ICT in Latin America: A Microdata Analysis

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ICT in Latin America

A microdata analysis

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Introduction

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Economic growth is based on technology, innovation and, more broadly, knowledge. In addition, Information and Communication Technologies (ICT) are key tools in promoting innovation activities, technology diffusion, and knowledge generation within societies. Indeed, as Information Society paradigm matures, effective use of ICT becomes an indispensable device in promoting sustainable growth. Unfortunately, Latin America is relatively delayed in these aspects and important economic policy debates in the region deal with how to promote its insertion in the knowledge-based economy. In order to examine determinants, characteristics and impacts of innovation activities and technology diffusion, the use of microdata is a promising field. In particular, the study of access, use, diffusion and effects of ICT across different economic agents —individuals, households and firms— may generate key insights for an adequate design, implementation and assessment of public policies.

In a conceptual perspective, we can understand ICT as a key dimension of technical change and economic growth. Several decades ago, Schumpeter (1942)[1] highlighted the *creative destruction* as a central process of technological and economic evolution of societies. This process states that at every moment there is a process of knowledge creation and destruction: new ideas, processes, products and organizational forms emerge; while others disappear. This process is, basically, driven by innovation. Since this wide conception of innovation, several scholars have proposed more precise definitions. For instance, Freeman and Perez (1988)[2] classified innovation activity among four different categories: i) incremental innovations; ii) radical innovations; iii) changes in the technological system and iv) changes in the techno-economic paradigm. In this perspective, ICT revolution corresponds to changes in the techno-economic paradigm, as ICT include a set of interconnected innovations which can not only modify the scene of a particular industry, but also of all industries and the whole economy. Thus, changes in techno-economic paradigms related to ICT revolution redefine trajectories not only in the technological and economic spheres, but also in the social scene. Thus, ICT are

1 Schumpeter, J. (1942). *Capitalism, Socialism and democracy*, New York: Harper
2 Freeman, C. and C. Perez (1988), "Structural crises of adjustment business cycles and investment behaviour", in Dosi, G., Freeman, C. Nelson, R. Silverberg, G. and L. Soete (Eds.) (1988), *Technical change and economic theory,* London: Pinter.

not only promoting the creative destruction process as a key underlying force behind technological and economic changes, but also generating opportunities and new ways of value creation that promote economic growth and development.

Indeed, the diffusion of ICT may have several implications, not only in economic terms but also in social and political dimensions. For example, the recent World Summit on Information Society highlighted ICT as a key device for development, with direct impacts on education, health and government services as well as on strengthening democracy, reducing poverty and promoting innovation and economic growth (WSIS, Geneva 2003 and Tunis 2005).[3] Nevertheless, it is increasingly clear that ICT access is not evenly distributed within and between countries, which leads to the conclusion that potential benefits are also not equally distributed among different populations. Indeed, potential impacts of ICT are neither automatic nor extended to all individuals. This uneven ICT access, as well as other economic and social differences, can be worsened if there are no adequate policies to guarantee digital access and benefits to all sectors of society. ICT present a great potential in the reduction of social and economic differences, but it could also deepen pre-existing economic or social inequalities. Thus, public policies must promote the positive role of new technologies.

Paradoxically, empirical evidence concerning determinants and diffusion channels of technology and knowledge in Latin America is scarce. In fact, there are important gaps and aspects to analyze and to understand with respect to both innovation and ICT at individual, household and firm levels. Innovation is a non-linear and complex process with the participation of several sources and subject to high degrees of uncertainty and cumulative learning. At the same time, there are several agents and institutions that participate directly or indirectly in the process, being the interrelations and links among them a central element of innovation outcomes. A better understanding of the phenomenon is a key aspect for the development of more inclusive and effective ICT public policies. The implementation of statistical and econometric techniques by using microdata, in particular from National Household Surveys and National Innovation Surveys, provide an interesting and appealing framework to analyze the phenomena in order to start closing this research gap.

This book is the final report of the ECLAC-IDRC project *Observatory for the Information Society in Latin American and the Caribbean* (OSILAC), *Third Phase*".[4] OSILAC III is a cooperating project between the International Development Research Centre (IDRC) and the Division of Production, Productivity and Management, ECLAC-UN, which aims at understanding the dynamics of the ICT evolution and revolution and producing evidence on its potential to promote socio-economic development. As such, microdata analysis

3 The World Summit on the Information Society (WSIS) was a conference about information, communication and information society sponsored by United Nations. The WSIS was held in two phases; the first phase took place in Geneva from 10 to 12 December 2003, and the second phase took place in Tunis, from 16 to 18 November 2005.

4 See http://www.eclac.cl/socinfo/osilac/

drawn from National Household Surveys and National Innovation Surveys in Latin America were used in the framework of the project in the attempt to reach those objectives. Both statistical information sources provide attractive potentialities in order to investigate not only determinants of innovation activities and technology diffusion, but also its economic impacts.

In recent years, the OSILAC project has fostered the development of a core list of internationally comparable indicators related to ICT diffusion in Latin America. OSILAC statistical information shows that although the usage of some ICT, such as mobile phones is growing widely, the level of use is still very far from those of developed countries, and broadband access indicators show that Latin America is not growing at their same rate. In addition, OSILAC has demonstrated that social and economic factors are powerful determinants of Internet access, particularly income level, education and geographical location. Interestingly, OSILAC's studies on ICT economic impacts have also confirmed that it is not the amount of equipment that triggers productivity and contributes to welfare, but rather the equipment use.[5] Thus, higher levels of capabilities among individuals and workers are essential to promoting ICT benefits among all population segments.

This book collects nine econometric articles organized in two main sections. Section A provides evidence with respect to ICT diffusion at household level in seven Latin American countries: Brazil, Chile, Costa Rica, Mexico, Paraguay, El Salvador and Honduras. These studies include cross-country comparisons, as statistical information used is similar across countries. Indeed, the analyses of this section are based on harmonized data from the OSILAC Online Statistical Information System,[6] which compiles indicators from National Household Surveys in Latin America. Then, section B presents empirical results concerning ICT impacts on firm performance for five Latin American countries: Argentina, Chile, Colombia, Peru and Uruguay. Unfortunately, these studies are not comparable and are only country specific because of the particular characteristics of each National Innovation Survey. The firm level studies were produced in collaboration with the Regional Dialogue on the Information Society Network (DIRSI).

In section A, Chapter I - "*Determinants of ICT Access*" analyzes different socioeconomic aspects that affect computer adoption and Internet penetration at household level in seven Latin American countries. It also investigates the role of other factors not commonly studied in the literature, such as complementarities of Internet use at different locations and geographical network effects. Chapter II - "*Patterns of Internet Use*" is the first cross-country analysis of Internet use in Latin America. In doing so, it disentangles

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5 Regional Seminar "*Growth, Productivity and ICT*", ECLAC Santiago de Chile 2007. Presentations are available at http://www.cepal.org/cgi-bin/getProd.asp?xml=/socinfo/noticias/noticias/0/27970/P27970.xml&xsl=/socinfo/tpl/p1f.xsl&base=/socinfo/tpl/top-bottom.xslt.

6 The Statistical System integrates harmonized data collected from National Household Surveys of 17 Latin American countries. The National Household Surveys contain some ICT variables which allow the calculation of the digital divide between and within countries by considering different income and educational quintiles, age cohorts and rural/urban areas. See http://www.eclac.org/tic/flash/default.asp?idioma=IN.

the determinants of Internet access from the determinants of Internet use. It is also the first exercise in the region that investigates the determinants of particular Internet use applications. Chapter III - "*The Impact of Internet Use on Individual Earnings*" uses matching techniques to examine the Internet impact on individual earnings. Given their different Internet use patterns, the analysis is implemented for salaried and self-employed workers separately. Finally, Chapter IV - "*Gender Differences in Internet Use*" analyzes the gender dimension as a determinant of the different Internet usage patterns.

In section B, Chapter I - "*ICT and Labour Productivity in Colombian Manufacturing Industry*" estimates ICT impact on labor productivity by using an extended Cobb-Douglas production function. It also investigates the role of both human capital and organizational changes in explaining labor productivity and potential complementarities with ICT investment in Colombia. Chapter II - "*ICT in Chilean Firms*" analyzes manager's perception with respect to ICT impact on sales, profits, margins and production costs in a reduced sample of Chilean firms. Chapter III - "*Science and Technology, ICT and Profitability in the Manufacturing Sector in Peru*" investigates the impact of different technological indicators on firm profitability. It also displays several aggregate indicators concerning the situation of technology and innovation activities in Peru. Similarly, Chapter IV - "*Impact of ICT and Innovation on Industrial Productivity in Uruguay*" studies the effect of ICT and innovation investment on productivity. Interestingly, it also investigates the effects of ICT and innovation activities on the demand for skilled and unskilled workers. This empirical exercise represents one of the first attempts in Latin America to test the complementarity or substitution hypotheses between ICT and employment at firm level. Finally, Chapter V - "*ICT, Organizational Change and Firm Performance: Evidence from Argentina*" investigates the relation between productivity and ICT, controlling for organizational changes and improvements in human capital. Additionally, it test the complementarity hypothesis among these firm dimensions.

Finally, section C - "*ICT in Latin America: Concluding Remarks*", resumes the main conclusions and implications derived from the empirical evidence. It also discusses the benefits and limitations of using microdata in analyzing ICT diffusion in Latin America and some relevant issues to investigate in the future research agenda. Overall, this book represents one of the first regional efforts in order to evaluate and understand different ICT dimensions by using microdata. It also provides empirical examples on the potentials and constraints of microdata analysis concerning ICT at individual, household and firm levels. Furthermore, it shows how the use of ICT microdata can support the proper design of public policies that promote the disseminations of ICT benefits across all population segments. This fact is also encouraging several Latin American countries to improve the implementation of different economic and social surveys that increasingly include innovation and technology dimensions.

A. ICT at household level in Latin America

I. Determinants of ICT access

Matteo Grazzi[1]
Sebastián Vergara

1. Introduction

It is widely recognized that the diffusion of Information and Communication Technologies (ICT) is an important engine of economic development. In particular, high levels of ICT diffusion in homes bring benefits to a country in terms of improving the quality of available human capital, increasing demand for technological goods and contributing to the democratization of political structures by providing a greater range of people with a better access to information. At the micro level, families using ICT gain several advantages, such as obtaining a more direct channel with institutions, improving communication efficiency and gaining technological skills which are increasingly important in the job-market. Having access to a home computer increases the probability of starting a new business (Fairlie, 2006), connecting ICT diffusion with some emerging issues of business analysis, like entrepreneurship. Especially in rural areas, households are often not only consumers but also productive units, whose productivity can be strongly enhanced by ICT. The diffusion of ICT can also play a major role in poverty reduction through better information dissemination, more effective promotion of social programs and improved governance and political participation.

The concept of *digital divide* has then become a relevant public issue, receiving increasing interest both at domestic and international level, taking different dimensions.[2] Indeed, researchers in developed countries —where ICT penetration is higher— have shifted their attention from the traditional distinction between *haves* and *have-nots* to the new concept of "digital inequality". It refers not only to mere differences in access, but also to different ICT usage patterns (DiMaggio and Hargittai, 2001). By contrast, in developing countries —where ICT diffusion is still at earlier stages— access issue remains an important open subject.

[1] The authors thank the statistical assistance of Cesar Cristancho and comments and suggestions from Barry Reilly and participants at the 6th European Meeting on Applied Evolutionary Economics (EMAEE) held in Jena, Germany, May 23-24, 2009. Usual disclaimers apply.

[2] In the early years of ICT diffusion, the digital divide was defined as "*the gap between individuals, households, business and geographic areas at different socio-economic levels with regard both to their opportunities to access ICT and to their use of the Internet for a wide variety of activities" (OECD, 2001).* More recently, the definition of digital divide has evolved and it includes the quality of access dimension. For example, ITU define it as *"the gap between those who benefit from digital technology and those who do not"* (ITU, 2005).

In this perspective, research on the drivers of technology diffusion in households is crucial in order to define appropriate public policies to address the *digital divide* in developing countries. Nevertheless, the existing empirical literature is mostly based on the experience of developed countries, while it is still missing a comprehensive analysis based on data at household or individual level in the developing world.[3] This paper contributes to fill this gap, evaluating the main socio-economic determinants of the presence of computer and Internet connection at household level in seven Latin American countries. Using data from *National Household Surveys*, we model the probability that a household has or has not adopted computer and Internet technologies in Brazil, Chile, Mexico, Costa Rica, El Salvador, Honduras and Paraguay. In addition to the traditional determinants found in the empirical studies, such as income, education, we also explore the role played by other factors commonly identified in theoretical discussions but not sufficiently investigated in empirical studies. In particular, we analyze the role played by geographical network effects, presence of students in the households and complementarities between Internet usage at work and at home.

The paper is organized as follows. Section 2 presents a literature review related to ICT access in households. Section 3 illustrates the overall patterns of ICT diffusion in Latin America. Then, Section 4 develops an economic and econometric framework to implement the empirical approach. Section 5 discusses estimation results and Section 6 concludes.

2. What do we know about ICT access at household level?

The existing economic literature on ICT penetration in households is still in its early stages. It basically consists of descriptive studies that highlight the correlation of access to technologies —computer, Internet, Broadband connection— with household or individual socioeconomic characteristics such as income, education, ethnicity, region and age (*e.g.* Kominski and Newburger, 1999; OSILAC, 2007). The analysis of the digital divide at different socio-economic dimensions is the central issue of the ICT literature at household level (Dewan and Riggins, 2005). In fact, regardless of the definition adopted, the strong policy implications of the digital divide has encouraged several institutions and scholars to analyze the phenomenon.

For instance, the National Telecommunication and Information Administration (NTIA) pointed out the correlation between education, income, race and age and ICT access in the US (NTIA, 2002, 1999; Leigh and Atkinson, 2001). Indeed, NTIA (2002) establishes that Internet is positively correlated with income, education and employment status.

3 For a cross-country analysis on ICT penetration determinants in developing countries, see Chinn and Fairlie (2006).

Additionally, young individuals are more likely to have ICT access. There is no evidence of a gender divide, while there are important ICT gaps among Whites, Asian Americans, Blacks and Hispanics. Likewise, Chaudhuri *et al*. (2005) used data from two surveys of US households to analyze socio-economic factors that affect Internet adoption. Despite the relevance of income and education, the results suggest that student condition is a significant determinant of Internet adoption, while African Americans and Hispanics are less likely to be online than other ethnic categories.

The causes of racial differences in rates of computer and Internet use in the U.S. are analyzed by Fairlie (2003 and 2004) and the results show that differences in income, education and occupation explain an important part —but not all— of the gap between Whites and other ethnicities. While no evidence is founded for price or school differences, language barriers could justify the remaining part of the gap. Ono and Zavodny (2007a) confirm the results obtained by Fairlie by analyzing the differences in ICT access and use between immigrants and natives in the U.S. They show that immigrants are less likely to have computer and Internet at home and that English ability plays an important role in this gap. Other studies with reference to the racial digital divide are Hoffman *et al*. (1997) and Hoffman and Novak (1998).

A number of recent studies have focused on the identification of other possible determinants of computer and Internet penetration. For example, Goolsbee and Klenow (2002) investigate the role of geographical network effects in the diffusion of home computers, finding that people in the U.S. are more likely to own computers in areas with higher computer penetration rates. Moreover, several contributions in the literature also recognize the role played by psychological factors and attitudes towards the adoption of new technologies. Demoussis and Giannakopoulos (2006a) for instance analyze the household characteristics which influence the probability of computer ownership in Greece. The panel nature of the data (1997-2001) allows them to verify the existence of serial persistence, which could be caused by genuine state dependence and by unobserved heterogeneity across households. They suggest that an important part of this heterogeneity —which accounts for almost a third of the variance of their model— can be explained by different household attitudes towards technology. Robertson *et al.* (2007) estimate a Probit model of residential computer adoption in the U.K. including a *proxy* variable measuring psychological attitudes towards technology. The results show that the variable is significant and it actually improves prediction outcomes of the empirical model when compared to the analogue standard Probit.

In an international comparison, Ono and Zavodny (2007b) examine the extent and causes of the digital inequality using microdata from US, Sweden, Japan, Korea and Singapore. The study examines patterns and determinants of computer and Internet access and use, focusing on cross-country differences along education levels, income, age and sex groups. Overall, the results are consistent with the hypothesis that the digital divide reflects pre-existing social and economic inequalities. Results, however, show no systematic relationship between pre-existing inequalities and differences in computer ownership. The authors interpret this by considering that computer diffusion has reached a critical mass in these countries. But demographic and socioeconomic characteristics are still related to whether an individual uses both a computer and Internet, even when access is granted. Remarkably, access to computers may ameliorate, but not necessarily erase, all digital divides.

The European Union (EU) has also been the subject of several studies concerning ICT diffusion. Vicente and Lopez (2006) analyze the determinants of ICT adoption at country and individual levels. Beyond the importance of income over both computer and Internet access, their results also confirm the relevance of university education. Moreover, Internet adoption seems to be only modestly sensitive to price. In another EU analysis, Demoussis and Giannakopoulus (2006b) use a cross-sectional dataset for 14 EU member states to estimate an ordered Probit model with selection bias. The empirical results confirm that Internet access is driven by household income, family size, education, age, gender, location and cost of Internet access. Additionally, Internet usage is positively influenced by household income, education and individual actions for skill acquisition and learning development. The authors also investigate ICT diffusion by sampling the data in north and south countries, and the evidence shows that there is a geographical digital divide in the EU. Interestingly, the decomposition analysis reveals that the differences in access for the two groups of countries are not related to differences in observed determinants. Indeed, the geographical divide is due to unobservables, such as cultural and attitudinal differences towards new technologies. Thus, the policy implication is that uniform policies across the EU will not be effective to reduce the digital divide.

In a regional perspective, Peres and Hilbert (2009) provide insightful information about ICT diffusion in Latin America. Among other issues, they focus on different dimensions of the digital divide with respect to the developed world. Interestingly, the gap is declining in the mobile technologies, while it is increasing in computer, Internet and broadband access.[4] Gutierrez and Gamboa (2008) focus on the digital divide among low income people in Colombia, Mexico and Peru. Their results show that education is the most important factor limiting ICT diffusion in these countries. Additionally, the authors establish the existence of a digital gender gap in Peru, but not in Mexico and Colombia. In a study of the Mexican case, Mariscal (2005) shows both the existence of high ICT inequality and that the digital divide is not narrowing. Furthermore, the paper discusses the social capital concept as a key aspect in the design and implementation of universal access policies.

A different strand of the literature deals with some theoretical considerations of the ICT diffusion. Greenstein and Prince (2005) for example analyze the geographic diffusion

[4] Additionally, Peres and Hilbert (2009) contains several articles analyzing the digital convergence, ICT industries, regulation, intellectual property rights and other ICT topics in Latin America.

of Internet in the US for both households and firms. Developed within the framework of economic diffusion theory, the authors conclude that the Internet diffused temporarily to several urban areas —because of the lack of maturity— with their complementary resources. Once the applications matured, the leading areas lost their position and ISP technologies diffused widely after commercialization. In an international framework, Venkatesch and Shih (2005) investigate how different diffusion theories —evolutionary, leapfrogging, structural and agentic— match the empirical ICT diffusion patterns in the US, Sweden and India. In particular, they seek to understand how technology is integrated into households. They find that no particular theory can exclusively explain all developments, and all four theories apply to different degrees. The authors argue that the determinants by which the computers are integrated into households are similar across cultures, stressing the role of impact and utilitarian outcomes.

3. ICT access in Latin America

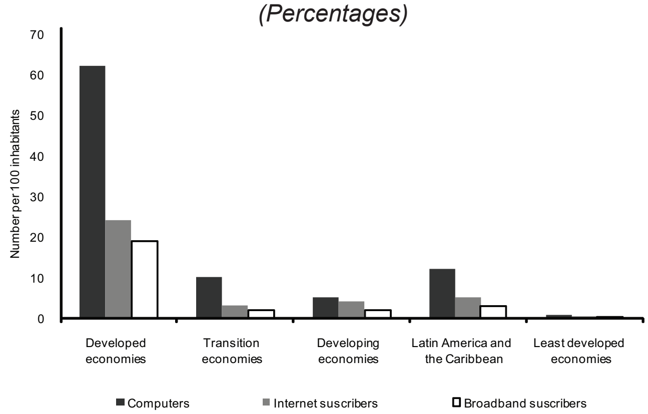
The ICT penetration in Latin America and the Caribbean is significantly below the developed world figures for computer and Internet (see Figure II.1). While the number of computers, Internet and broadband subscribers in the developed countries are respectively 62, 24 and 19 per 100 individuals, in Latin America and the Caribbean all these indicators are below 12 per 100 individuals. And, as discussed by Peres and Hilbert (2009), the gap is not narrowing in these dimensions. Figure II.1 also shows that the diffusion of computers in the region is clearly higher than in the rest of the developing World, but the access to Internet and broadband is similar.[5]

Latin America itself reflects different patterns of diffusion, both between and within countries. Sub-regionally, South America shows higher levels of penetration than Central America and the Caribbean. For example, considering the ITU's ICT Development Index (IDI), Argentina, Chile and Uruguay are the better ranked Latin American countries in 2007 (ranking 47, 48 and 49 respectively), while Haiti is by far the worst ranked (136th, after Mauritania and Benin) (ITU, 2008).[6]

5 However, these data should be taken with caution, as the comparison is made by using the average of all developing countries. For example, Latin American countries have a disadvantage situation in ICT access in comparison with East Asian countries (ITU, 2008).

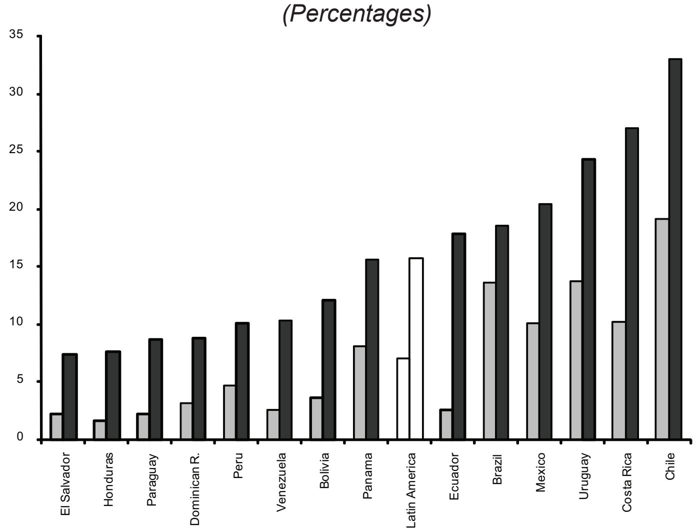
6 The ICT Development Index (IDI) compares ICT developments in 154 countries over a five-year period from 2002 to 2007. It is created by combining 11 indicators related to ICT access, use and skills into a single measure.

Figure II. 1
ICT diffusion across regions in the world
(Percentages)



Source: International Communication Union (ITU) (2008), Statistics Bulletin, www.itu.com.

Figure II. 2
Latin America: ICT household access[a]
(Percentages)



Source: Authors' elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/.
[a] The average for Latin America corresponds to the average of the displayed countries.

Focusing on access, Figure II.2 presents data on computer and Internet penetration at household level for 14 Lain American countries. On average, penetration rates for computer and Internet for Latin America at household level are 15% and 7%, respectively. Clearly, there is an important heterogeneity in the ICT diffusion across countries. While

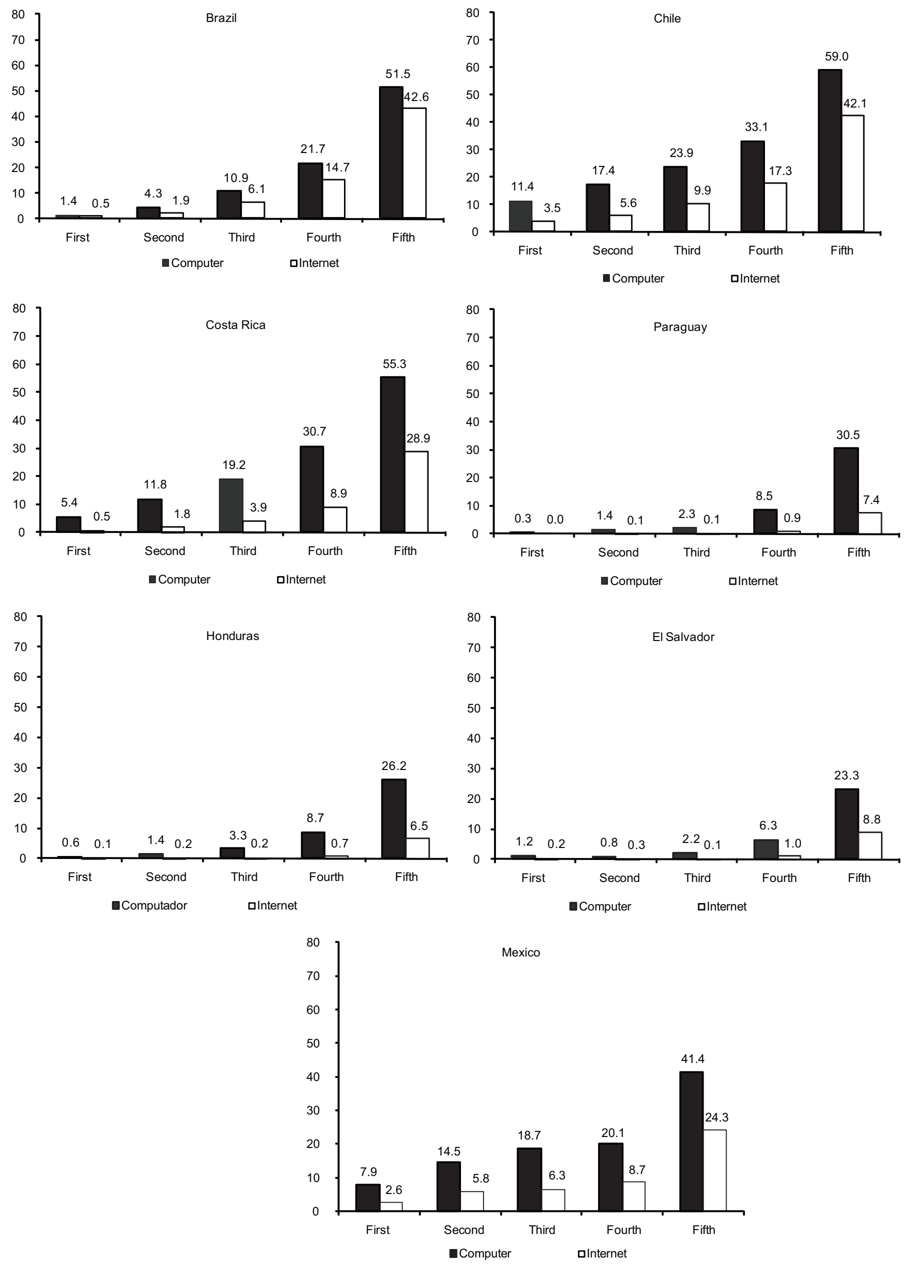
Chile, Costa Rica, Mexico and Brazil show relatively high penetration rates; Honduras, El Salvador and Paraguay are the most digitally delayed countries. In sum, countries with higher computer adoption rates tend to have higher Internet access rates, but there are also some special cases. Costa Rica, for example, not only has a relatively high level of computer adoption, but also a large gap between computer and Internet adoption rates.[7] By contrast, Brazil presents the lowest gap among computer and Internet adoption: the difference between computer and Internet penetration rates is just 4.9%.

Figure II.3 shows ICT penetration rates by per capita income quintiles for the seven Latin American countries analyzed. Not surprisingly, higher income quintiles are associated with higher ICT penetration rates. For example, in the Chilean case, the penetration rates for computer and Internet adoption in the fifth quintile are 59% and 42%, and in Costa Rica these participations are 55% and 29%, respectively. Furthermore, differences in ICT penetration are not homogeneous along subsequent quintiles, and the fifth income quintile concentrates the bulk of ICT penetration. For instance, in Honduras, the computer adoption rate rises from 0.6% in the first income quintile to 8.7% in the fourth, and then it jumps strongly to 26% in the fifth quintile. Such discontinuity is more evident in countries with limited ICT diffusion, such as El Salvador, Honduras and Paraguay. In countries with higher rates of technology diffusion - namely Brazil, Chile, Mexico and Costa Rica - the concentration of ICT diffusion in the fifth quintile is relatively lower.

Likewise, the distribution of ICT across educational groups follows a similar pattern: higher educational quintiles have higher access to both computer and Internet (see Figure II.4). For example in Mexico, the computer and Internet adoption rates in the first quintile are 1.3% and 0.2%; while the penetration rates in the fifth quintile are 60% and 34%, respectively. In El Salvador, the non homogeneity in the ICT diffusion is particularly clear. In fact, the increasing ICT diffusion for subsequent educational quintiles is relatively homogeneous from the first (0.2%) until the fourth quintile (4%), but it increases more than proportionally in the fifth quintile (26%).

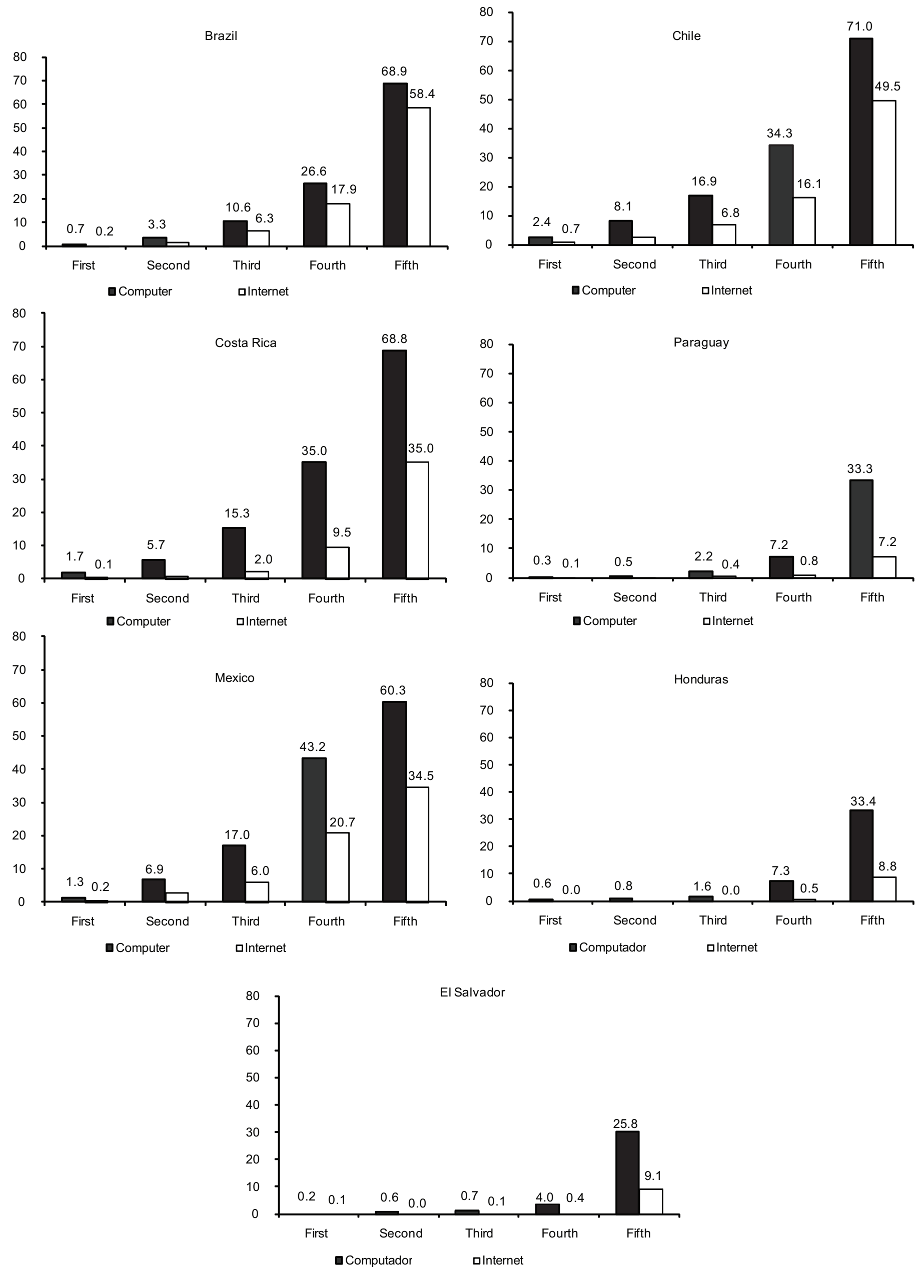
[7] Ecuador also evidences a striking situation: while it shows a relatively high computer adoption rates (18%) –higher than Latin American average-, it also shows a very low Internet access rate (2.5%).

Figure II. 3
Latin America: ICT Access by Income Quintiles
(Percentages)



Source: Authors' elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/.

Figure II. 4
Latin America: ICT access by education quintiles[a]
(Percentages)



Source: Authors' elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/.
[a] Correspond to quintiles of the average education years of adults within the household.

Table II.1
Household access to computer and Internet
(*Percentages*)

Country	Access/Year	2000	2001	2002	2003	2004	2005	2006
Brazil	Computer	.	12.6	14.2	15.3	16.3	18.5	.
	Urban	.	14.6	16.3	17.5	18.9	21.4	.
	Rural	.	1.2	1.6	1.8	2.1	2.7	.
	Internet	.	8.5	10.3	11.4	12.2	13.6	.
	Urban	.	9.9	12.0	13.2	14.3	15.9	.
	Rural	.	0.5	0.5	0.7	0.8	1.1	.
Chile	Computer	17.5	.	.	24.9	.	.	33.1
	Urban	19.9	.	.	28.0	.	.	36.6
	Rural	2.2	.	.	4.7	.	.	9.9
	Internet	8.4	.	.	12.6	.	.	19.2
	Urban	9.6	.	.	14.3	.	.	21.6
	Rural	0.8	.	.	1.3	.	.	2.8
Costa Rica	Computer	13.7	17.3	19.9	.	23.7	26.6	.
	Urban	19.3	23.7	27.3	.	31.4	35.2	.
	Rural	5.3	7.5	8.7	.	12.0	13.7	.
	Internet	4.0	5.3	7.2	.	.	10.0	.
	Urban	6.0	7.8	10.5	.	.	14.3	.
	Rural	1.0	1.6	2.3	.	.	3.7	.
El Salvador	Computer	2.7	4.5	5.2	5.5	6.0	.	7.6
	Urban	4.3	7.1	8.1	8.5	9.1	.	11.4
	Rural	0.1	0.2	0.3	0.5	0.8	.	1.0
	Internet	1.0	1.6	2.3	2.4	2.0	.	2.4
	Urban	1.7	2.5	3.6	3.8	3.1	.	3.7
	Rural	0.0	0.0	0.0	0.1	0.1	.	0.1
Honduras	Computer	.	.	.	5.2	5.4	6.3	7.6
	Urban	.	.	.	10.1	10.6	11.7	14.1
	Rural	.	.	.	0.5	0.4	1.0	1.4
	Internet	.	.	.	.	1.4	1.5	1.4
	Urban	.	.	.	.	2.8	2.9	2.8
	Rural	.	.	.	.	0.1	0.2	0.1
Mexico	Computer	.	.	.	.	18.0	18.6	20.6
	Urban	.	.	.	.	.	.	30.3
	Rural	.	.	.	.	.	.	13.2
	Internet	.	.	.	.	8.7	8.9	10.1
	Urban	.	.	.	.	.	.	15.7
	Rural	.	.	.	.	.	.	5.7
Paraguay	Computer	.	5.2	5.4	6.2	6.4	8.7	.
	Urban	.	8.9	8.4	10.0	10.0	13.2	.
	Rural	.	0.5	0.8	0.9	1.2	1.7	.
	Internet	.	1.0	1.2	1.8	1.0	1.7	.
	Urban	.	1.7	2	3.1	1.7	2.7	.
	Rural	.	0.1	0.0	0.0	0.1	0.1	.

Source: OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/.

Table II.1 presents computer and Internet penetration rates by urban and rural areas for the period 2000-2006, subject to data availability in each country. Three messages emerge from the data. First, all countries evidence an increasing trend in both computer and Internet penetration rates, but the level and speed of the technology diffusion is heterogeneous. On one extreme, Chile's computer adoption rate increased from 17% in 2000 to 33% in 2006, and the Internet access rate grew from 8% to 19%. On the other, Paraguay's computer adoption rate rose from 5% in 2001 to 9% in 2005, and the Internet access rate from 1% to 1.7%. Second, the ICT diffusion is not uniform throughout different geographic locations within each country. Indeed, there is a clear digital divide between rural and urban areas. For instance, in Costa Rica —the country with the lowest urban-rural gap— urban computer and Internet penetration rates are 35% and 14%, and rural access rates are 14% and 4%, respectively. Thus, the computer penetration rate in rural areas is 39% of the penetration rate in urban areas; and this participation decreases to only 26% in the Internet access. Third, the digital divide among rural and urban areas is narrowing across time, but this reduction is slow. In Chile, while the Internet penetration rate was 9.6% in the urban areas and 0.8% in the rural areas in 2000, five years later these figures were 21.6% and 2.8%, respectively (see Table II.1). Therefore, the ratio of rural/urban penetration rates increased from 8% to 13%.

4. Methodology and empirical approach

(a) Methodology

In this section we describe the economic model and the econometric approach used to analyze the determinants of ICT diffusion at the household level in Latin American countries. Following Fairlie (2004) and Vicente and Lopez (2006), we use a linear random utility function to model the household's decision to have or to have not a computer at home. The utility associated with each of the two situations is assumed to be a linear function of a set of household's socio-economic characteristics (X_i) and of a stochastic term which represents unobservables and measurement errors (ε_i). Hence, the indirect utility of household *i* associated with having a computer ($U_{i,H}$) and not having it ($U_{i,N}$) can be expressed as:

$$U_{i,H} = X_i \beta_H + \varepsilon_{i,H} \qquad (1)$$
$$U_{i,N} = X_i \beta_N + \varepsilon_{i,N} \qquad (2)$$

Thus, household *i* will choose to have a computer if the utility associated with it is higher than the utility associated with not having: $U_{i,H} > U_{i,N}$. If we define a variable Y so that $Y_{i,H}$ = 1 if the i^{th} household owns a computer and $Y_i = 0$ if it does not, the probability that the *i*th household has access to a computer is $\Pr(Y_{i,H} = 1) = \Pr(U_{i,H} > U_{i,N}) = \Phi[X_i(\beta_H - \beta_N)]$, where Φ is the cumulative distribution function of $[\varepsilon_{i,H} - \varepsilon_{i,N}]$. Normalizing the utility of having no computer at home to zero ($U_{i,N} = 0$), we derive the empirical equation for computer adoption:

$$\Pr(Y_{i,H} = 1) = \Pr(U_{i,H} > 0) = \Phi[X_i \beta] \qquad (3)$$

In a similar way, we can derive an equation to model the probability of household *j* to have an available Internet access at home:

$$\Pr(Y_{j,C} = 1) = \Pr(U_{j,C} > 0) = \Phi[X_j \theta] \qquad (4)$$

Where $U_{j,C}$ is the indirect utility associated with being connected to the Internet. Therefore, we can empirically analyze household determinants of computer adoption and Internet access through the estimation of β and θ parameters in the empirical equations (3) and (4). A common econometric approach to estimate these equations by Maximum Likelihood Estimation (MLE) is the Probit model.

The Probit model assumes that the error term is normally distributed with mean 0 and variance σ equal to 1, and $\Phi(.)$ corresponds to the cumulative distribution function for a standard normal random variable. Nonetheless, a possible problem with this approach is that it does not consider the correlation between household choices regarding both computer and Internet. On the one hand, computer adoption is a prerequisite to having an available Internet connection at home. On the other hand, the decision of owning a computer can be founded on the fact that it is a necessary previous step to Internet connection. The key point is that a computer can be either a final good itself or just a requirement to access the web, depending on the characteristics of the computer usage in the household.

The linkage between these decisions raises an important econometric consideration. In fact, maximum likelihood estimation of two correlated Probit models seems to be a not fully efficient econometric procedure choice, as it ignores the correlation between the error terms. A natural extension of Probit estimation that takes into account such a correlation is the Bivariate Probit model (BiProbit) (Greene, 2003). In the Bivariate Probit model, the error terms follow a bivariate normal distribution:

$$\Pr(Y_{i,H} = 1) = \Phi\,[X_i \beta] \tag{5}$$
$$\Pr(Y_{j,C} = 1) = \Phi\,[X_j \theta] \tag{6}$$
$$E(\varepsilon_{i,H}) = E(\varepsilon_{j,C}) = 0 \;;\; V(\varepsilon_{i,H}) = V(\varepsilon_{j,C}) = 1 \;;\; Cov(\varepsilon_{i,H}, \varepsilon_{j,C}) = \rho \tag{7}$$

The Bivariate Probit model is estimated by Full-Information Likelihood (FIML) procedure, using a likelihood function specified in terms of a standard normal bivariate probability function. The correlation between the two equations provides a more coherent framework to model both household decisions. However, given the nature of the data, the BiProbit methodology does not capture fully the character of the correlation (selection) between the variables in our empirical case. In fact, computer adoption determines completely the possibility of Internet connection, selecting the households that can actually adopt it. Thus, the sample of households that have an Internet connection is not random and this characteristic of the data generates biased estimations (Heckman, 1979).

An econometric framework that deals with this problem is the Bivariate Probit model with sample selection. This approach adapts the Heckman two-step procedure to this dichotomous case (Van de Ven, *et al.*, 1981). Intuitively, the Heckman procedure deals with sample selection as a specification problem. Hence, it attempts to solve it by inserting a *proxy* variable that captures the omitted part of the sample truncated mean that is attributable to selection. The Bivariate Probit with sample selection model (*HeckProbit*) is specified as follows:

$$\Pr(Y_{j,C} = 1) = \Phi\,[X_j\theta + \varphi\lambda_i] \qquad (8)$$

Where λ correspond to the inverse Mill's ratio (*Heckman correction term*). In this equation, the dependent variable is observed if $U_{i,H} = X_i\beta_H + \varepsilon_{i,H} > 0$. Thus, the computer adoption equation is specified as a selection equation. Empirically, the procedure follows the next steps. First, the selection equation is estimated by maximum likelihood. Then, this estimation is used to construct the inverse Mill's ratio ($\lambda=\phi(X'_i\theta)/\Phi(X'_i\theta)$) by using the pseudo residuals. These pseudo residuals represent the unobserved factors that determine household decision on having computer access. Finally, the selection correction term λ is included in the Internet Probit equation, which is also estimated by using maximum likelihood procedure.

(b) Empirical approach

The data used in the econometric section come from the National Household Surveys conducted in seven Latin American Countries in 2005 and 2006. All surveys are representative at national level and cover a wide range of socio-economic variables at individual and household level, such as income, education, age, occupation, household characteristics and location, among others. Additionally, the surveys include questions concerning computer adoption and Internet access (See Table II.2). Considering the methodological issues discussed in the previous section, our empirical approach for the analysis of ICT determinants in each country is based on the following two equations:

$$\Pr(\mathit{Computer}=1) = \Phi\,(\alpha + \beta_0{*}\mathit{Income}_i + \beta_1{*}\mathit{Education}_i + \beta_2{*}\mathit{Users}_i + \beta_3{*}\mathit{Rural}_i + \beta_4{*}\mathit{Work}_i + \beta_5{*}\,\mathit{Students}_i + \beta_6{*}\,\mathit{Network}_{i,C}) \qquad (9)$$

$$\Pr(\mathit{Internet}=1) = \Phi\,(\alpha + \beta_0{*}\mathit{Income}_i + \beta_1{*}\mathit{Education}_i + \beta_2{*}\mathit{Users}_i + \beta_3{*}\mathit{Rural}_i + \beta_4{*}\mathit{Work}_i + \beta_5{*}\mathit{Students}_i + \beta_6{*}\mathit{Network}_{i,I}) \qquad (10)$$

Where *Income* corresponds to the household per capita equivalent income,[8] *Education* is the household education level measured by the average level of educational years

[8] In order to take into account economies of scale in household consumption, we use an equivalent income measure, which is the total household income divided by the so-called LIS (Luxembourg Income Studies) equivalence scale. It is defined as the square root of the number of household members (Atkinson *et a*l., 1995).

of adults (age ≥ 18)[9] and *Users* is the number of individuals potentially capable to use computers in the household (age ≥ 6). These variables are expected to be the most relevant socio-economic and demographic determinants of ICT diffusion. Income has been identified in the literature as a key factor in explaining technology adoption, operating on the household budget constraint (Vicente and Lopez, 2006). It is supposed to be particularly important in developing countries, where technology diffusion is still in an early stage and prices are relatively high. Also education should be an important driver of adoption, as it is necessary to be somehow technologically-skilled in order to use computers and Internet proficiently. Finally, the larger the number of potential users in the household, the higher should be the household's utility of adoption.

The *Students* variable corresponds to the proportion of students in the household, which is supposed to influence positively the probability of having a computer and Internet connection. In fact, students usually have more advanced technological skills and may constitute an important engine of technologies adoption. *Rural* controls for the area (urban or rural) where the household is located. *Work* is a dummy variable that represents the use of Internet at work of at least one individual in the household and tests for complementarities between ICT usage at work and at home.[10]

Finally, the $Network_{C,I}$ variables correspond to the computer and Internet penetration rates in the geographical area where the household is located. These variables test for the existence of network effects for computer and Internet diffusion, respectively. The hypothesis is the presence of local positive spillovers of existing computer owners and Internet subscribers on households considering technology adoption, *i.e.* households located in more digitally advanced regions have reduced costs or increased benefits in having a computer or Internet access. Costs of adoption may be reduced because of the possibility to learn about the technology from neighbors, while additional benefits could derive from the possibility to share software and to communicate with a larger number of people (Goolsbee and Klenow, 2002). The existence of network effects is tested at specific geographical levels for each country due to different data availability: we calculate penetration rates by Federative Unit in Brazil and Mexico, by Province in Chile, by Planning Region in Costa Rica and by Department in El Salvador, Honduras and Paraguay.

An important contribution of this study is that all independent variables concern the household as a whole. On the contrary, most of the previous literature includes in the regressions variables that refer to household head characteristics (*e.g.* Singh, 2004). This approach implicitly assumes that the decisions about computer and Internet adoption are taken by the household head. However, this is a weak argument, especially

9 The household education level is represented by an index representing the average educational attainment of adults (age ≥18). The exception is Mexico because of the lack of information concerning educational years of individuals.
10 See Table A.1 in Appendix for a description of variables.

in developing countries where households are larger and a higher number of income earners can belong to the same household. Then, we argue that decision-making is a more complex process and that it is preferable to model the decision of ICT access on the characteristics of the entire household, considering it as a single unit.

Table II.2
Household surveys description

Country	Year	Survey	Institution	Households
Brazil	2005	Pesquisa Nacional por Amostra de Domicílios (PNAD)	Fundacao Instituto Brasileiro de Geografia e Estatistica (IBGE)	116 452
Chile	2006	Encuesta de Caracterización Socioeconómica Nacional (CASEN)	Ministerio de Planificación Nacional (MIDEPLAN)	73 720
Costa Rica	2005	Encuesta de Hogares de propósitos múltiples (EHPM)	Instituto Nacional de Estadística y Censos (INEC)	11 549
El Salvador	2005	Encuesta de Hogares de Propósitos Múltiples. (EHPM)	Dirección General de Estadística y Censos (DIGESTYC)	16 343
Honduras	2006	Encuesta Permanente de Hogares de Propósitos Múltiples (EPHPM)	Instituto Nacional de Estadística (INE)	20 581
Mexico	2006	Encuesta Nacional sobre Disponibilidad y Uso de las Tecnologías de la Información en los Hogares (ENDUTIH)	Instituto Nacional de Estadística y Geografía (INEGI)	4 813
Paraguay	2005	Encuesta Permanente de Hogares (EPH)	Dirección Nacional de Estadísticas, Encuestas y Censos (DNEEC)	4 464

Source: Authors' elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/.

In order to check the robustness and sensitiveness of the econometric results, our estimation strategy follows three steps. First, we estimate independently computer and Internet Probit models. Then, Bivariate Probit is performed to take into account the correlation between the error terms of both equations. Finally, the BiProbit methodology is extended, considering computer adoption as a sample selection problem for the Internet access.

5. Estimations results

The estimation results are organized by country: Tables II.3 to II.9 present the Probit Estimations for both computer and Internet adoption equations. The first column of each set of results contains the baseline estimation, to which we add sequentially the *dummy* variables (*Students*, *Work* and *Rural*) and the network effects variable in order to check the sensitiveness of the estimated coefficients. We follow this procedure for all countries. As an overall conclusion, estimation results seem to be quite robust to different specifications.

Table II.3
Brazil - determinants of computer and Internet adoption: probit estimations

Model	Computer adoption			Internet adoption		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-6.930 (116.43)***	-6.684 (105.24)***	-7.084 (107.10)***	-7.407 (113.85)***	-7.115 (102.25)***	-7.589 (103.81)***
$Income_i$	0.583 (68.11)***	0.580 (63.91)***	0.544 (59.14)***	0.587 (63.33)***	0.580 (58.67)***	0.549 (54.33)***
$Education_i$	0.182 (78.74)***	0.145 (59.12)***	0.150 (59.30)***	0.188 (71.76)***	0.149 (52.93)***	0.156 (53.90)***
$Users_i$	0.163 (41.97)***	0.103 (23.63)***	0.114 (25.44)**	0.175 (41.51)***	0.117 (24.58)***	0.131 (26.36)***
$Students_i$	.	0.763 (28.38)***	0.813 (29.78)***	.	0.699 (23.77)***	0.763 (25.46)***
$Work_i$	.	0.431 (28.72)***	0.426 (28.27)***	.	0.456 (28.36)***	0.450 (27.94)***
$Rural_i$	.	-0.407 (13.23)***	-0.348 (11.15)***	.	-0.616 (12.76)***	-0.569 (11.68)***
$Network_{i,C}$	.	.	0.026 (34.37)***	.	.	0.035 (35.38)***
Log-Likelihood	-33 560.284	-32 311.295	-31 616.756	-27 102.608	-25 967.501	-25 262.844
Wald Chi^2 (Prob> Chi^2)	16 900.17 (0.000)	19 502.24 (0.000)	18 681.37 (0.000)	15 062.88 (0.000)	16 536.21 (0.000)	16 140.95 (0.000)
Pseudo-R^2	0.394	0.416	0.429	0.411	0.436	0.451
Observations	114,961	114,961	114,961	114,959	114,959	114,959

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis. * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table II.4
Chile - determinants of computer and Internet adoption: probit estimations

Model	Computer adoption			Internet adoption		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-8.496 (45.98)***	-9.403 (47.80)***	-9.529 (45.78)***	-10.192 (44.53)***	-10.992 (40.18)***	-11.101 (41.31)***
$Income_i$	0.423 (27.32)***	0.526 (29.93)***	0.514 (29.29)***	0.528 (25.26)***	0.618 (26.19)***	0.595 (25.66)***
$Education_i$	0.207 (46.55)***	0.169 (35.63)***	0.168 (35.54)***	0.188 (32.31)***	0.158 (24.98)***	0.155 (24.97)***
$Users_i$	0.162 (24.08)***	0.066 (8.89)***	0.066 (8.82)***	0.156 (20.73)***	0.084 (9.69)***	0.082 (9.51)***
$Students_i$	.	1.651 (29.43)***	1.656 (29.52)***	.	1.224 (18.90)***	1.251 (19.38)***
$Work_i$	.	0.079 (2.70)***	0.077 (2.62)***	.	-0.567 (1.73)*	-0.616 (1.89)*
$Rural_i$	.	-0.386 (16.59)***	-0.295 (12.17)***	.	-0.716 (20.73)***	-0.504 (13.90)***
$Network_{i,C}$	.	.	0.008 (7.69)***	.	.	0.019 (14.37)***
Log-Likelihood	-32 732.764	-30 953.202	-30 865.692	-24 670.435	-23 650.492	-23 317.691
Wald Chi^2 (Prob> Chi^2)	4 454.20 (0.000)	5 971.33 (0.000)	5 986.75 (0.000)	3 512.46 (0.000)	4 079.64 (0.000)	4 116.67 (0.000)
Pseudo-R^2	0.299	0.337	0.339	0.312	0.340	0.350
Observations	73,432	73,432	73,432	73,238	73,238	73,238

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis. * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table II.5
Costa Rica - determinants of computer and Internet adoption: probit estimations

Model	Computer adoption			Internet adoption		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-7.695 (23.11)***	-7.828 (21.06)***	-8.319 (22.00)***	-10.682 (21.15)***	-10.685 (19.98)***	-10.93 (20.02)***
$Income_i$	0.383 (13.39)***	0.424 (13.41)***	0.422 (13.16)***	0.574 (13.26)***	0.590 (12.95)***	0.586 (12.78)***
$Education_i$	0.207 (31.15)***	0.165 (22.40)***	0.087 (6.65)***	0.181 (19.92)***	0.163 (16.22)***	0.161 (15.91)***
$Users_i$	0.164 (14.37)***	0.093 (7.20)***	0.087 (6.65)	0.134 (8.90)***	0.109 (6.45)***	0.106 (6.21)**
$Students_i$	.	0.994 (11.53)***	1.040 (11.83)***	.	0.399 (3.91)***	0.411 (4.02)***
$Work_i$	.	0.231 (4.44)***	0.190 (3.60)***	.	0.029 (0.48)	0.002 (0.04)
$Rural_i$	.	-0.203 (5.75)***	-0.101 (2.84)***	.	-0.180 (3.57)***	-0.114 (2.23)**
$Network_{i,C}$	.	.	0.019 (11.56)***	.	.	0.028 (5.37)***
Log-Likelihood	-4 412.370	-4 266.933	-4 203.333	-2 408.7535	-2 390.102	-2 375.893
Wald Chi^2 (Prob> Chi^2)	1780.09 (0.000)	1989.37 (0.000)	1997.29 (0.000)	1144.31 (0.000)	1179.22 (0.000)	1155.91 (0.000)
Pseudo-R^2	0.330	0.352	0.362	0.352	0.357	0.360
Observations	11 259	11 259	11 259	11 263	11 263	11 263

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis. * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table II.6
El Salvador - determinants of computer and Internet adoption: probit estimations

Model	Computer adoption			Internet adoption		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-6.607 (14.53)***	-6.363 (13.73)***	-6.486 (14.08)***	-7.581 (13.73)***	-7.513 (12.59)***	-7.665 (12.64)***
$Income_i$	0.519 (5.50)***	0.509 (5.68)***	0.510 (5.72)***	0.529 (5.99)***	0.530 (5.67)***	0.527 (5.64)***
$Education_i$	0.189 (11.82)***	0.165 (11.22)***	0.164 (11.19)***	0.201 (8.78)***	0.197 (8.07)***	0.195 (7.97)***
$Users_i$	0.137 (7.91)***	0.108 (5.73)***	0.109 (5.81)***	0.095 (2.99)***	0.081 (2.22)**	0.082 (2.25)**
$Students_i$	.	0.614 (4.77)***	0.617 (4.80)***	.	0.245 (1.14)	0.259 (1.21)
$Work_i$	.	0.449 (2.75)***	0.443 (2.73)***	.	-0.098 (0.58)***	0.102 (0.60)
$Rural_i$	.	-0.376 (3.77)***	-0.328 (3.22)***	.	-0.588 (3.25)	-0.523 (2.85)***
$Network_{i,C}$	.	.	0.014 (1.95)*	.	.	0.057 (1.71)*
Log-Likelihood	-2 621.023	-2 561.907	-2 558.496	-1 018.941	-1 009.487	-1 006.401
Wald Chi^2 (Prob> Chi^2)	498.09 (0.000)	590.34 (0.000)	587.34 (0.000)	186.17 (0.000)	202.59 (0.000)	201.34 (0.000)
Pseudo-R^2	0.402	0.415	0.416	0.445	0.450	0.452
Observations	16 343	16 343	16 343	16 343	16 343	16 343

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis. * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table II.7
Honduras - determinants of computer and Internet adoption: probit estimations

Model	Computer adoption			Internet adoption		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-6.419 (32.84)***	-6.010 (27.98)***	-6.074 (28.22)***	-8.694 (22.10)***	-8.377 (20.22)***	-8.449 (20.36)***
$Income_i$	0.367 (14.95)***	0.349 (13.23)***	0.345 (12.99)***	0.457 (10.12)***	0.448 (9.37)***	0.439 (9.13)***
$Education_i$	0.194 (33.09)***	0.163 (26.17)***	0.160 (25.68)***	0.226 (20.44)***	0.202 (16.89)***	0.197 (16.50)***
$Users_i$	0.087 (11.08)***	0.063 (7.05)**	0.062 (6.89)***	0.089 (5.70)***	0.063 (3.60)***	0.058 (3.27)***
$Students_i$	.	0.530 (7.80)***	0.532 (7.82)***	.	0.328 (2.66)***	0.332 (2.66)***
$Work_i$	.	0.364 (6.67)***	0.336 (6.13)***	.	0.465 (6.20)***	0.411 (5.36)***
$Rural_i$	.	-0.407 (8.46)***	-0.377 (7.66)***	.	-0.544 (3.44)***	-0.494 (3.09)***
$Network_{i,C}$	.	.	0.013 (4.13)***	.	.	0.096 (4.47)***
Log-Likelihood	-3 459.637	-3 367.541	-3 360.1503	-817.869	-790.866	-784.131
Wald Chi^2 (Prob> Chi^2)	2 208.96 (0.000)	2 204.15 (0.000)	2 222.43 (0.000)	727.17 (0.000)	703.54 (0.000)	713.00 (0.000)
Pseudo-R^2	0.370	0.386	0.388	0.456	0.474	0.479
Observations	20 581	20 581	20 581	20 283	20 283	20 283

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis. * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table II.8
Mexico - determinants of computer and Internet adoption: probit estimations

Model	Computer adoption			Internet adoption		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-6.116 (15.61)***	-5.981 (13.91)***	-6.307 (14.24)***	-7.023 (13.54)***	-6.432 (11.48)***	-6.863 (12.16)***
$Income_i$	0.214 (4.43)***	0.232 (4.34)***	0.211 (3.88)***	0.322 (5.36)***	0.300 (4.56)***	0.277 (4.24)***
$Education_i$	4.719 (17.83)***	4.072 (14.02)***	4.117 (13.91)***	3.886 (14.06)***	3.206 (11.25)***	3.334 (11.37)***
$Users_i$	0.179 (9.04)***	0.117 (5.25)***	0.121 (5.30)***	0.155 (6.42)***	0.114 (4.06)***	0.125 (4.33)***
$Students_i$	.	1.094 (6.78)***	1.084 (6.67)***	.	0.596 (3.16)***	0.580 (3.04)***
$Work_i$	.	0.459 (4.54)***	0.454 (4.44)***	.	0.431 (4.12)***	0.424 (4.05)***
$Rural_i$	.	-0.122 (1.53)	-0.042 (0.52)	.	-0.231 (2.21)**	-0.135 (1.24)
$Network_{i,C}$	.	.	0.019 (4.14)***	.	.	0.039 (4.82)***
Log-Likelihood	-1 725.518	-1 651.021	-1 633.567	-1 092.258	-1 059.422	-1 036.500
Wald Chi^2 (Prob> Chi^2)	465.85 (0.000)	548.32 (0.000)	538.51 (0.000)	297.45 (0.000)	305.30 (0.000)	327.11 (0.000)
Pseudo-R^2	0.291	0.322	0.329	0.277	0.299	0.314
Observations	4 811	4 811	4 811	4 813	4 813	4 813

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis. * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table II.9
Paraguay - determinants of computer and Internet adoption: probit estimations

Model	Computer adoption			Internet adoption		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-13.320 (12.83)***	-13.118 (11.66)***	-13.074 (11.72)***	-12.960 (10.67)***	-12.058 (9.13)***	-12.024 (9.02)***
$Income_i$	0.690 (8.98)***	0.693 (8.33)***	0.677 (8.18)***	0.658 (7.48)***	0.618 (6.42)***	0.606 (6.29)***
$Education_i$	0.176 (12.82)***	0.145 (9.66)***	0.142 (9.39)***	0.116 (5.54)***	0.092 (3.81)***	0.077 (3.17)***
$Users_i$	0.124 (5.91)***	0.080 (3.37)***	0.076 (3.17)***	0.055 (1.92)*	0.042 (1.27)	0.021 (0.64)
$Students_i$	.	0.828 (4.92)***	0.892 (5.23)***	.	-0.026 (0.10)	0.131 (0.47)
$Work_i$	.	0.300 (2.51)**	0.272 (2.26)**	.	0.329 (2.10)**	0.311 (1.88)*
$Rural_i$	.	-0.311 (2.81)***	-0.186 (1.60)*	.	-0.329 (2.10)**	-0.316 (1.08)
$Network_{i,C}$	.	.	0.017 (3.98)***	.	.	0.078 (4.81)***
Log-Likelihood	-776.752	-752.322	-746.266	-255.445	-249.223	-237.133
Wald Chi^2 (Prob> Chi^2)	417.69 (0.000)	438.72 (0.000)	476.56 (0.000)	140.63 (0.000)	149.84 (0.000)	194.78 (0.000)
Pseudo-R^2	0.408	0.427	0.431	0.336	0.352	0.383
Observations	4 461	4 461	4 461	4 461	4 461	4 461

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis. * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Additionally, we extend the analysis for Brazil, Chile and Costa Rica by estimating Bivariate Probit models (Tables II.10 to II.12).[11] In this case, the decision of which Bivariate Probit model is preferred is not straightforward.[12] Econometrically, the BiProbit is estimated simultaneously by Full Information Maximum Likelihood and the Bivariate Probit with sample selection —*HeckProbit*— is estimated in two steps, as described in the previous section. In this sense, the former is more efficient, although, considering the sample selection characteristic of the data, the *HeckProbit* methodology fit the household decisions better.[13] The main issue concerning this methodology is the identification of the selection equation (Greene, 2003). In fact, consistent estimation in *HeckProbit* model requires using at least one variable that affects the computer adoption but not the Internet access, in order to permit the proper identification of the estimated coefficient on the

[11] We include three countries in this estimation set because in these cases the likelihood functions of the Bivariate estimations converged.

[12] In those countries where we only implement Probit regressions, the preferred model is the one including all the explanatory variables

[13] Both methodologies are sensitive to departures from normality in the error tem. In fact, the *HeckProbit* estimation of φ in equation (11) is sensitive to normality in ε_i, given the construction of λ_i invokes the normal assumption ($\lambda_i=\varphi(Z'_i\theta)/\Phi(Z'_i\theta)$). The non-normality in the context of bivariate probability distribution functions is more complex, and it would be much easier remaining within the two-step framework.

selectivity term.[14] Empirically, however, this is not an easy task. We use the computer penetration rate variable (*Network*$_{i,C}$) in the selection equation for identification purposes.

Table II.10

Brazil - determinants of computer adoption and Internet access: bivariate probit estimations

Method	**Bivariate probit**		**Bivariate probit w/ sample selection (HeckProbit)**	
Variables	**Computer (1)**	**Internet (2)**	**Computer (3)**	**Internet (4)**
Constant	-7.055 (109.02)***	-7.572 (106.34)***	-7.084 (107.07)***	-3.172 (5.04)***
Income$_i$	0.540 (60.25)***	0.554 (55.67)***	0.544 (59.07)***	0.293 (6.86)***
Education$_i$	0.150 (59.30)***	0.153 (55.45)***	0.150 (59.29)***	0.076 (6.10)***
Users$_i$	0.115 (26.00)***	0.122 (23.47)***	0.114 (25.32)***	0.068 (5.27)***
Students$_i$	0.808 (29.87)***	0.750 (25.21)***	0.813 (29.77)***	0.259 (3.52)***
Work$_i$	0.425 (28.28)***	0.449 (28.14)***	0.426 (28.27)***	0.254 (6.40)***
Rural$_i$	-0.354 (11.38)***	-0.582 (12.38)***	-0.347 (11.13)***	-0.655 (8.24)***
Network$_{i;C;}$	0.026 (34.83)***	.	0.026 (34.38)***	.
Network$_{i;;I}$	.	0.036 (36.52)***	.	0.027 (9.32)***
Log-Likelihood	-19 363 638		-19 400 000	
ρ = *Cov*($\varepsilon_{1,}$ ε_2)	0.99		-0.05	
Atanh ρ = ½ *ln(1+ρ/1-ρ)*	3.738 (17.36)***		-0.054 (0.46)	
Wald Chi^2 (Prob> Chi^2)	21 603.92 (0.000)		142.33 (0.000)	
Wald Test of indep. eqs. *(ρ =0)* *Chi^2 (1)* *(Prob> Chi^2)*	301.323 (0.000)		0.22 (0.642)	
Censored observations	.		94 725	
Uncensored observations	.		20 234	
Observations	114 959		114 959	

Source: Author's own elaboration.

*Note: z-statistics in absolute value with robust standard errors in parenthesis; * Significant at 10%; ** Significant at 5%, *** Significant at 1%*

[14] In the econometric literature there is no consensus on this point, as some scholars argue that identification on the basis of functional form is empirically adequate. This argument, based on non-linearity of the Probit methodology, is not fully convincing. Indeed, any worthwhile identification should be achieved through the use of appropriate exclusion restrictions (Puhani, 2000).

Table II.11
Chile - determinants of computer adoption and Internet access: bivariate probit estimations

Method	Bivariate probit		Bivariate probit w/ sample selection (HeckProbit)	
Variables	**Computer (1)**	**Internet (2)**	**Computer (3)**	**Internet (4)**
Constant	-9.602 (45.78)***	-11.059 (43.67)***	-9.619 (46.43)***	-10.898 (28.23)***
$Income_i$	0.515 (29.17)***	0.591 (27.19)***	0.517 (29.60)***	0.592 (23.74)***
$Education_i$	0.168 (35.74)***	0.155 (27.06)***	0.168 (35.65)***	0.146 (14.10)***
$Users_i$	0.069 (9.53)***	0.078 (8.50)***	0.069 (9.22)***	0.078 (7.20)***
$Students_i$	1.635 (29.92)***	1.242 (19.42)***	1.652 (29.39)***	1.091 (7.62)***
$Work_i$	0.729 (2.49)**	-0.058 (1.83)*	0.074 (2.53)**	-0.090 (2.22)**
$Rural_i$	-0.296 (12.13)***	-0.496 (13.86)***	-0.300 (12.08)***	-0.517 (12.41)***
$Network_{i;C;}$	0.009 (9.13)***	.	0.009 (8.01)***	.
$Network_{i;;I}$	.	0.021 (16.17)***	.	0.024 (11.01)***
Log-Likelihood	-2 633 513.2		-2 633 113	
ρ = Cov(ε_1, ε_2)	0.99		0.80	
Atanh ρ = ½ ln(1+ρ/1-ρ)	4.121 (10.41)***		1.087 (3.06)***	
Wald Chi^2 (9) (Prob> Chi^2)	7387.55 (0.000)		2768.57 (0.000)	
Wald Test of indep. eqs. (ρ =0) *Chi^2 (1)* *(Prob> Chi^2)*	108.316 (0.000)		9.37 (0.002)	
Censored observations	.		58 411	
Uncensored observations	.		14 827	
Observations	73 238		73 238	

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis; Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table II.12
Costa Rica - determinants of computer adoption and Internet access: bivariate probit estimations

Method	Bivariate probit		Bivariate probit w/ sample selection (HeckProbit)	
Variables	**Computer (1)**	**Internet (2)**	**Computer (3)**	**Internet (4)**
Constant	-8.293 (22.00)***	-10.849 (20.74)***	-8.294 (22.01)***	-10.851 (20.75)***
$Income_i$	0.419 (13.04)***	0.579 (13.00)***	0.418 (13.05)***	0.579 (13.02)***
$Education_i$	0.162 (21.84)***	0.163 (15.85)***	0.162 (21.77)***	0.163 (15.72)***
$Users_i$	0.091 (6.96)***	0.091 (5.00)*	0.091 (6.96)***	0.091 (4.99)***
$Students_i$	1.028 (11.90)***	0.382 (83.79)***	1.028 (11.90)***	0.381 (3.75)***
$Work_i$	0.189 (3.60)***	0.027 (0.46)***	0.189 (3.60)***	0.026 (0.44)
$Rural_i$	-0.103 (2.92)***	-0.141 (2.84)***	-0.103 (2.92)***	-0.142 (2.84)***
$Network_{i;C;}$	0.019 (11.80)***	.	0.019 (11.79)***	.
$Network_{i;;I}$	.	0.032 (6.24)***	.	0.032 (6.14)***
Log-Likelihood	-581,630.44		-581,628.7	
ρ = *Cov*($\varepsilon_{1,}$ ε_2)	0.99		0.95	
Atanh ρ = ½ *ln*(1+ρ/1-ρ)	3.411 (8.19)***		1.869 (4.85)***	
Wald Chi² (9) (Prob> Chi²)	2 484.41 (0.000)		1 131.44 (0.000)	
Wald Test of indep. eqs. (ρ =0) *Chi² (1)* *(Prob> Chi²)*	67.085 (0.000)		23.51 (0.000)	
Censored observations	.		8 838	
Uncensored Observations	.		2,421	
Observations	11 259		11 259	

Source: Author's own elaboration.
Note: z-statistics in absolute value with robust standard errors in parenthesis, Significant at 10%;
*** Significant at 5%, *** Significant at 1%.*

The estimation results for Brazil confirm that income and education are relevant determinants of computer and Internet adoption (see Table II.3). Indeed, the coefficients associated to *Income*, *Education* are positive, significant at 1% and fairly stable across the different specifications. Additionally, the positive and significant coefficients of *Users* for both computer and Internet equations capture two different effects. First, the larger the number of potential users, the higher the household utility associated with having a computer and Internet. Second, larger households are able to spread fixed costs on more individuals, increasing *de facto* their per capita income. With respect to the *Students* and *dummy* variables (*Work* and *Rural*), results show that estimated coefficients are significant and with the *a priori* expected signs. In fact, a higher proportion of students in the household raise the probability of ICT access, confirming the hypothesis that computer and Internet are often used for education purposes. Also, there is evidence of complementarities between Internet usage at work and both computer and Internet adoption at home, with coefficients positive and significant at 1%. This relation, which has not received enough attention in the economic literature, shows how earlier stages of Internet adoption process in households are strongly influenced by its use in the workplace. A possible explanation refers to the fact that individuals need some training in order to exploit the potentialities of the Internet. Thus, Internet use at work increases the utility of having it at home and then the probability for households to be connected. As expected from the descriptive statistics, households located in rural areas are less likely to own a computer and to have Internet, showing the relative difficulty of gaining access to ICT in these areas.

Table II.13

Marginal effects - Brazil[a]

Variables	Computer (1)	Internet (2)
Income$_i$	0.073 (52.61)***	0.036 (38.34)***
Education$_i$	0.020 (61.42)***	0.010 (43.28)***
Users$_i$	0.015 (26.74)***	0.008 (26.15)***
Students$_i$	0.110 (28.66)***	0.504 (22.81)***
Work$_i$	0.070 (22.42)***	0.039 (19.49)***
Rural$_i$	-0.039 (14.03)***	-0.026 (19.22)***
Network $_{I, C}$	0.003 (32.08)***	0.002 (28.01)***

Source: Authors elaboration based on column (1) and (2) of table 10;
*[a] In the case of dummy variables, the marginal effect correspond to a discrete change of the variable from 0 to 1, i.e. impact effects; Coefficients z-statistics with robust standard errors in parenthesis, * Significant at 10%;*
*** Significant at 5%, *** Significant at 1%.*

Interestingly, the *Network* variable is positive and significant at 1%. This suggests the existence of network effects associated to the computer and Internet adoption at the federation level. Thus, households are more likely to own a computer and to have Internet access if a high percentage of people in their federative units have larger ICT penetration. Also, the magnitude of the network effects seems to be higher for Internet than for computer. This fact can be interpreted considering the nature of the Internet technology itself, which is increasingly more useful as the Net is diffused in a particular geographical area.

The Bivariate Probit estimations for Brazil are displayed in Table II.10. Regardless some size differences in the coefficients —they are relatively lower for the Internet equation in the Bivariate Probit model with sample selection with respect to the Probit estimations— the results are quite similar in their implications. Strikingly, the estimations for the Bivariate Probit and *HeckProbit* models show that, while both equations are in fact correlated, there is not a statistical selection problem between computer and Internet decisions. Given the nature of these results, we take as our preferred estimation for Brazil the Bivariate Probit model.

The Probit estimations for Chile are displayed in Table II.4. Similarly to Brazil, estimated coefficients are consistent across different specifications. For instance, variables such as *Income*, *Education*, and *Users* are relevant determinants of both computer and Internet adoption. The variable *Students*, *Work* and *Rural* are also significant at 1% and with the expected sign for the computer adoption. Indeed, households with a higher proportion of students, located in urban areas and in which at least one member of the households uses Internet at work are more likely to have a computer. In the case of Internet adoption, the results are similar with the only exception of the *Work* variable coefficient, which is negative and significant at 10%. This suggests that, in Chile, using Internet at work may be a good substitute for being connected at home. In other words, people who are online at the office may present a lower utility to also be connected at home. Additionally, Probit results confirm that there are network effects that influence both computer and Internet adoption. One important detail is that, once it is included the network effect variable in the regressions, the coefficients associated to the *Rural* variable reduce their magnitude. Intuitively, we think that the *Network* variable may capture some of the characteristics of the rural areas, introducing some difficulties in isolating their specific effect.

Table II.11 presents the estimation results by applying the Bivariate Probit procedures in Chile. In both cases, the estimates clearly confirm that the two equations are correlated, and that there is a sample selection problem that must be taken into account. In fact, the (estimated) correlation between the two error terms ρ is positive and statistically different from zero. This implies that unobservables affecting the computer adoption are positively correlated to unobservables affecting Internet adoption. Also in this case the results largely confirm those obtained with the Probit estimations, including the negative and significant estimated coefficient of the *Work* variable. Given that the estimation procedures confirm the sample selection problem, our preferred model in the case of Chile is the *HeckProbit* model.

In order to avoid repetitive result descriptions and considering the robustness of the estimations, we briefly comment the results the remaining countries, emphasizing only those that are remarkable or intuitively not expected *a priori*. In Costa Rica, for example, the results concerning *Income*, *Education*, *Users*, *Rural* and *Network* variables are expected. However, it is noticeable that the use of Internet at work does not affect the use of Internet at home; being the coefficient associated to the *Work* variable not significant. The Bivariate Probit estimations reflect the correlated structure and the sample selection problem of the data. Then, our preferred estimation is the *HeckProbit* model. The *HeckProbit* estimation confirms Probit results and the non-relevance of the *Work dummy* variable. Additionally, in the case of El Salvador, the Probit estimations show that traditional variables such as *Income*, *Education*, *Users*, *Students*, *Work*, and *Rural* are important determinants of computer diffusion, while the network effects variable is significant, but only at 10%. In the case of Internet adoption, the results point out that *Student* and *Work* variables are not relevant drivers of technology diffusion. Again, the network effects are significant only at the lowest confidence level. There is a probability that the extremely low penetration rates of ICT in El Salvador have not reached minimum level necessary to make network effects a stronger driver of adoption.

Honduras estimation results show that all variables are significant at 1% and they are rather stable across the different specifications. In Mexico, similarly to the Chilean case, the inclusion of the network effects variable into the estimations cause a reduction on the magnitude of the estimated coefficient of the *Rural* variable. The correlation between these two variables makes it difficult to disentangle the rural and network effects. Finally, Paraguay estimations reflect similar results concerning *Income* and *Education* (see Table II.9). However, some outcomes must be mentioned: *Users* variable does not affect the Internet adoption and *Students* variable affects computer adoption but not Internet access. Furthermore, once the *Rural* variable is added to the estimation, it proves to be an important driver for both computer and Internet adoption. Nevertheless, when the network variable is included, the estimation presents again the correlation problem with the *Rural* variable. In fact, in the Internet equation, *Rural* variable is not significant anymore. As discussed in Grazzi and Vergara (2008), this should be subject of further research.

Given the nature of a non-linear model, the marginal effects are not directly obtainable from the estimated coefficients. For illustration purposes, we only present the marginal effects for Brazil, by using the Probit estimations (see Table II.13).[15] For instance, the marginal effect for income is 0.073 for computer adoption. This implies that an increase of 1% in household per capita income generates a raise of 7.3% in the probability of having computer access, on average and *ceteris paribus*. Similarly, households with 1% higher average education are 2% more likely to own a computer, on average and *ceteris paribus*. Also, households located in rural areas are 3.9% and 2.6% less likely to have computer and Internet adoption, respectively. Correspondingly, households having at least one member who uses Internet at work are 7.0% and 3.9% more likely to have computer and Internet adoption respectively.

Overall, the econometric evidence is plausibly consistent across the different methodologies, and there are some convincing findings (see Table I.14). First, income and education are the strongest determinants of ICT access. As expected, households with higher income levels and higher average education are more likely to adopt computer and Internet. Similarly, households with students and with a larger number of potential users present higher probability of having ICT access. Second, households located in rural areas are less likely to have ICT access, showing their relatively weak position with respect to the diffusion of technologies. In addition, geographical network

[15] In a Probit model, the marginal change is a function of the rest of covariates, and it is computed commonly in the mean of the variables. In fact, the marginal effect is given by the expression: *We compute the marginal effects at the mean of variables.*

effects also seem to be at work at the geographical level and independent of the urban/rural areas. Third, with the exception of Chile, where the use of Internet at work seems to be a substitute for home access, all other countries demonstrate evidence of complementarities between Internet usage at work and ICT access at home.

Table II.14
Determinants of computer and Internet adoption: resume table

Country	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Variable				**Computer adoption**			
$Income_i$	+	+	+	+	+	+	+
$Education_i$	+	+	+	+	+	+	+
$Users_i$	+	+		+	+	+	+
$Students_i$	+	+	+	+	+	+	+
$Work_i$	+	+	+	+	+	+	+
$Rural_i$	-	-	-	-	-		-
$Network_{i,C}$	+	+	+	+	+	+	+
				Internet adoption			
$Income_i$	+	+	+	+	+	+	+
$Education_i$	+	+	+	+	+	+	+
$Users_i$	+	+	+	+	+	+	
$Students_i$	+	+	+		+	+	
$Work_i$	+	-			+	+	+
$Rural_i$	-	-	-	-	-		-
$Network_{i,I}$	+	+	+	+	+	+	+

Source: Author's elaboration based on preferred estimation model for each country.

6. Concluding remarks

The remarkable impact of ICT diffusion over different development dimensions deserves a deeper analysis of its patterns. This study focuses on the determinants of computer adoption and Internet access at household level in seven Latin American countries. Several conclusions can be drawn from both descriptive and parametric analysis. First, computer and Internet penetration in Latin America is relatively low if compared with developed world. Nevertheless, there is high ICT access heterogeneity across countries. Second, the descriptive analysis shows that ICT penetration is greatly concentrated in specific income and education groups and urban areas. Thus, diffusion of technologies seems to replicate other socioeconomic inequalities. Additionally, cross-country comparisons suggest that countries with lower ICT diffusion levels present higher penetration inequality across income and educational groups.

The econometric estimations reveal other important features of ICT diffusion. The traditional determinants, such as income, education, and urban/rural areas are confirmed to be relevant drivers of technology diffusion in the region. Larger households and households with students are more likely to have ICT access. Moreover, there is general evidence of the presence of complementarities between Internet use at different locations and geographical network effects, though not in all countries. Finally, network effects seem to play an important role in ICT diffusion, independently from household location in rural or urban areas.

The importance of ICT in the development path justifies an increasing effort by international institutions, academia and scholars to achieve a better understanding of their diffusion process. The use of microdata provides an appealing framework to analyze this phenomenon. In fact, its implications can clearly support the design of public policies towards to expand the benefits of ICT in all segments of population.

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8. Appendix

Table A.1
Description of variables

Variable	Description
Pr(Computer=1)	Dichotomous computer adoption variable: 1:yes; 0: no.
Pr(Internet=1)	Dichotomous Internet adoption variable: 1:yes; 0: no.
$Income_i$	Log_n of equivalent household income.
$Education_i$	Average of adults education years (age>17)
$Users_i$	Number of potential users of ICT (age>6).
$Network_{i,C}$	Percentage of households with computer, by geographic location.[a]
$Network_{i,I}$	Percentage of households with Internet connection, by geographic location.[a]
$Students_i$	Proportion of students in the household.
$Work_i$	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.
$Rural_i$	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.

Source: Authors' calculation based on National Household Surveys.
[a] *Brazil is divided in 27 Federative Units; Chile is divided in 50 Provinces; Costa Rica is divided in 6 Planning Regions; El Salvador is divided in 14 Departments: Honduras is divided in 18 Departments; Mexico is divided in 32 Federative Units and Paraguay is divided in 15 departments.*

II. Patterns of Internet use

Matteo Grazzi[1]

1. Introduction

It has been estimated that nearly a quarter of the World population use the Internet today, more than doubling from 11% in 2002 (ITU, 2009). Such impressive growth reflects the fact that individuals connected to Internet gain considerable economic benefits. In particular, being on-line is related to obtaining better access to information and knowledge, improving communication efficiency and enriching one's own technological skills, which are increasingly important in the job market. For example, in the United States, an average wage gain of 13.5 percent for on-the-job Internet usage was estimated (Goss and Phillips, 2002). Moreover, the majority of jobs in new sectors require computer and Internet skills and the Internet is also becoming an increasingly relevant tool of job-searching. In addition, *netizens*, *i.e.* on-line individuals, have new spaces for political participation and more direct access to government services, gaining time and efficiency.

Therefore, the diffusion of the Internet is becoming a priority for policy-makers across the World and in particular in developing countries, where Internet may also constitute a valuable instrument in fighting poverty. In fact, access to on-line resources is claimed to help poverty reduction through several channels, such as promoting education in remote areas via distance-learning, disseminating health, welfare and environmental information and making social programs more effective.[2] Nevertheless, although the early vision was generally optimistic in seeing Internet as an equalizing factor both at international and at domestic level, successive scholars have called the policy makers' attention on the risk that the advantages of Internet use were limited to those who were yet advantaged in terms of economic resources and social status. Consequently, inequalities in Internet access and use might exacerbate pre-existing inequalities rather than ameliorate them (Di Maggio *et al*., 2004).

[1] The author thanks Cesar Cristancho for statistical assistance and Martha Sánchez and Sebastián Vergara for comments, references and discussions. Usual disclaimers apply.

[2] For a comprehensive literature review on ICT and poverty, see Adeya (2002).

Thus, the identification of the drivers of Internet diffusion in a country is a relevant issue in order to correctly evaluate its impact on the society and to design effective public policies. In this perspective, this paper contributes to the existing literature in several areas, using data from National Household Surveys of seven Latin American Countries: Brazil, Chile, Costa Rica, El Salvador, Honduras, Mexico and Paraguay.[3] First, it helps to identify determinants of Internet use, decoupling them from those of access. Second, it is the first cross-country analysis of Internet use in Latin America using microdata. Finally, it is one of the very few studies (and the first on developing countries, to the best of our knowledge) which analyzes the determinants of adoption of specific Internet applications. The study is structured as follows. Section 2 summarizes the relevant literature. Section 3 shows descriptive statistics on Internet use in Latin America. Section 4 introduces the economic model and the econometric strategy and Section 5 presents and discusses the estimation results. Finally, section 6 concludes.

2. Background

In the earliest stage of the Internet diffusion, the main concern of researchers was the availability of connection. Most of the relevant literature focused on the identification of determinants of access to the Internet, referring with this concept to the actual possibility to connect to the Net if a person wants to. Many studies showed persistent differences by socio-economic categories, constituting a solid empirical base for public policies directed to close the internal digital divide (*e.g.* NTIA, *various issues*). Later, the concept of access has been broadened, and in some cases “access” became synonymous with “use”, conflating opportunity and choice. In fact, access is mainly driven by resources, while use is related to demand (Di Maggio *et al*, 2004). In other words, in order to connect and to fully exploit the potentialities of Internet, it is not sufficient that individuals have access to, but that they must also have the capability and the interest to use it. As new technologies increase its penetration in a country and its access price decreases, it becomes increasingly easier for individuals to gain access. A high level of access may not necessarily imply the same level of use (Ono and Zavodny, 2003). In the United States, for example, 20% of individuals living in households with an available Internet connection never use it (Lenhart *et al*., 2003). Figures in Latin America are even more

[3] In Brazil, data come from *Pesquisa Nacional por Amostra de Domicílios* (PNAD), by *Fundacao Instituto Brasileiro de Geografia e Estatistica* (IBGE); in Chile from *Encuesta de Caracterización Socioeconómica Nacional* (CASEN) by *Ministerio de Planificación Nacional* (MIDEPLAN); in Costa Rica from *Encuesta de Hogares de propósitos multiples* by *Instituto Nacional de Estadística y Censos* (INEC); in El Salvador from *Encuesta de Hogares de Propósitos Múltiples* (EHPM) by *Dirección General de Estadística y Censos* (DIGESTYC); in Honduras from *Encuesta Permanente de Hogares de Propósitos Múltiples* (EPHPM) by *Instituto Nacional de Estadística* (INE); in Mexico from *Encuesta Nacional sobre Disponibilidad y Uso de las Tecnologías de la Información en los Hogares* (ENDUTIH) by *Instituto Nacional de Estadística y Geografía* (INEGI) and in Paraguay from *Encuesta Permanente de Hogares* (EPH) by *Dirección Nacional de Estadísticas, Encuestas y Censos* (DNEEC).

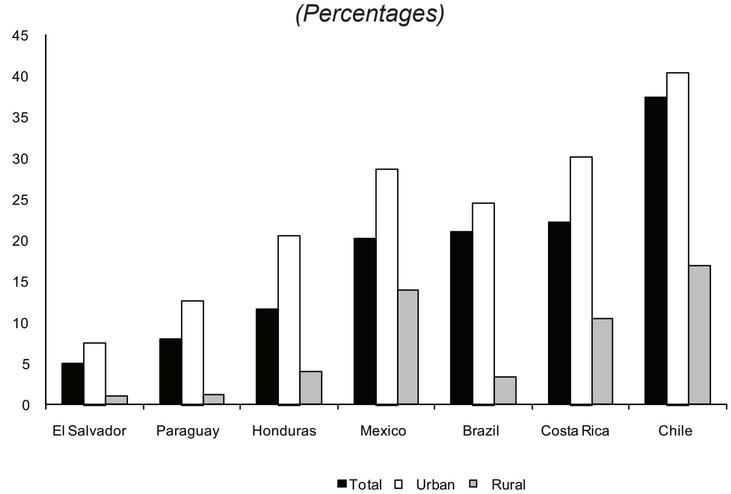
impressive. For instance, in Paraguay, El Salvador and Mexico, over 30% of people having a home Internet connection, do not use the Internet at all (see Table III.1).

Table III.1
Internet use-nots living in households with available connection
(*Percentages*)

Country	Year	Not using Internet at any location	Not using Internet at home
Brazil	2005	26.5	28.5
Chile	2006	23.8	35.2
Costa Rica	2005	29.1	37.5
Dominican Rep.	2005	19.2	22.5
El Salvador	2006	39.0	53.4
Honduras	2006	26.2	38.2
Mexico	2006	34.7	40.9
Nicaragua	2006	22.2	42.0
Panama	2006	24.0	45.7
Paraguay	2006	37.8	50.6
Peru	2007	27.3	37.9
Uruguay	2006	23.7	30.4

Source: Author's elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/

Figure III.1
Latin America: individual Internet use
(Percentages)



Source: Author's elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash.

Nevertheless, only few scholars have analyzed the determinants of Internet use decoupled from those of Internet access. They have mainly explored just the dichotomous distinction between individuals who use the Internet and individuals who do not, showing controversial results. On the one hand, some studies found empirical evidence for the hypothesis that, once access is granted, differences in Web use tend to disappear. For example, Hoffmann and Novak (1998) used data from a nationally representative survey of Internet use in the United States, in order to assess the impact of race on computer access and Internet use. Analyzing patterns of Internet use among students, they found that there are no differences in usage rates among white and Afro-American students when they have an available computer at home. On the contrary, among students without a computer at home, whites are much more likely to use the Internet at other locations, such as school, work or public access points. Therefore, they conclude that access translates into usage with respect to race*, i.e.* that whites are more likely than African Americans to use the Web just because they are more likely to have access to it (Hoffmann *et al.*, 2000).

On the other hand, some scholars established the existence of socioeconomic inequalities in Internet use, even when access is granted. In fact, the existence of a gap between access and use has been confirmed by several studies. For instance, Ono (2005) —in a comparative empirical work on Japan, South Korea and Singapore— shows a clear digital divide across demographic groups in computer and Internet use. This evidence allows the author to argue that access does not translate into usage, at least in the countries examined. Previously, Shashaani (1997) had examined the gender gap in computer use among U.S. college students, finding that the primary user of home computers were predominantly males. She concluded that the presence of a computer at home itself may not encourage women to use it. Ono and Zavodny (2003) find that, among the sub-sample of people living in households with an available computer in the United States, women were less likely to use Internet in 1997, but they became more likely in 2001. Instead, among individuals living in Japanese households with computers, women are less likely to use computers and Internet than men in both 1997 and 2001. Considering that Japan is one of the industrialized countries where gender inequality is most pronounced, these results are not surprising and suggest that differences in Internet use may be rooted in preexisting inequalities (Di Maggio *et al.*, 2004). With regard to differences between ethnic groups, Fairlie (2004), using data from a nationally representative survey in the US, shows the existence of a racial digital divide in the United States. Employing a Multinomial Logit regression, he demonstrates that all minorities are less likely to use Internet than whites conditional to having an available home computer.

More recently, some studies consider not only the decision of individuals for personal use but also the extent and the patterns of Internet usage. Demoussis and Giannakopoulos (2006) use cross-sectional European microdata for the period 2002-2003 in order to identify the factors that shape both the decision of individuals to use the Internet and the extent to which they use it. Their results show that the probability of use is primarily influenced by gender, age, education, family size, household income, cost of Internet access and regional characteristics. Moreover, they find a positive correlation between the decision to use Internet and the extent of usage. In other words, individuals with higher probabilities of use report higher rates of usage, *ceteris paribus*. On the contrary, Goldfarb and Prince (2008) argue that the patterns of Internet adoption and usage differ significantly. In particular, they find that high-income, educated people are more likely to adopt the Internet but that conditional upon adoption; they spend considerably less time online. Given this result, their explanation refers to the lower opportunity costs of leisure time for low-income individuals. To test this hypothesis, they analyze Internet usage of specific applications, and the fact that low-income people are more likely to execute time-consuming and inexpensive activities online is taken as evidence of the role played by the opportunity cost of leisure time.

Furthermore, Goldfarb and Prince (2008) extend their work analyzing usage of different Internet applications. Controlling for other demographic variables, they found that low-income Americans are more likely to use the Internet for chat, online games and health information, while high-income Americans are more likely to use it for e-commerce. They argue that the differences in application usage according to income gives moderate support to the hypothesis that Internet usefulness varies across demographic groups. Few other empirical studies investigate specific Internet applications. For instance, in the context of on-line banking, Lambrecht and Seim (2006) find heterogeneity in the consumer patterns of adoption and usage. They show that adoption depends on the user's comfort with technology, but the intensity of usage depends on the user's banking needs. In another contribution related to Internet banking, Lee *et al.* (2003) show that socioeconomic variables are significant predictors of the consumer perception of having access to computer banking. However, the adoption of Internet banking is more likely to be determined by the technology consumer's perception than by their socioeconomic characteristics.

3. Internet use in Latin America

Similar to the World trend, Latin America also shows an impressive growth in Internet users, which jumped from 500,000 in 1995 to 124 million people in 2007 (ITU, 2008). However, the region evidences high heterogeneity with respect to penetration of the Internet, and Internet use rates largely differ both between and within countries. At country level, ITU estimates that in 2007, use rates vary from under 10% in Nicaragua and Honduras to over 30% in Brazil, Chile and Costa Rica (ITU, 2008). These figures are substantially confirmed by the descriptive statistics based on microdata (see Figure III.1 and Table III.2). At sub-national level, there is clear evidence of an urban-rural divide in terms of Internet use across countries. For example, in Brazil, Internet urban penetration rate in 2005 is 24.5%, while it is only 3.4% in rural areas. And in countries with lower penetration levels, this gap is even more pronounced: Internet use rate in 2006 in urban Paraguay is 12.6%, but in rural areas is only 1.2%. In Honduras, urban areas show a penetration rate of 20.4% while only 4% of people living in rural areas use Internet. Moreover, the urban-rural gap does not seem to be narrowing over time. For example, considering data for Chile in 2000 and 2006, the divide is smaller in relative terms, but wider in absolute ones.[4] Indeed, in 2000 the Internet use rates in urban and rural areas were 21.3% and 5.9%, respectively, with a difference of 15.4 percentage points. This difference increased to 23.4 points in 2006 (see Table III.2).

Table III.2
Latin America: Individual Internet Use
(Percentages)

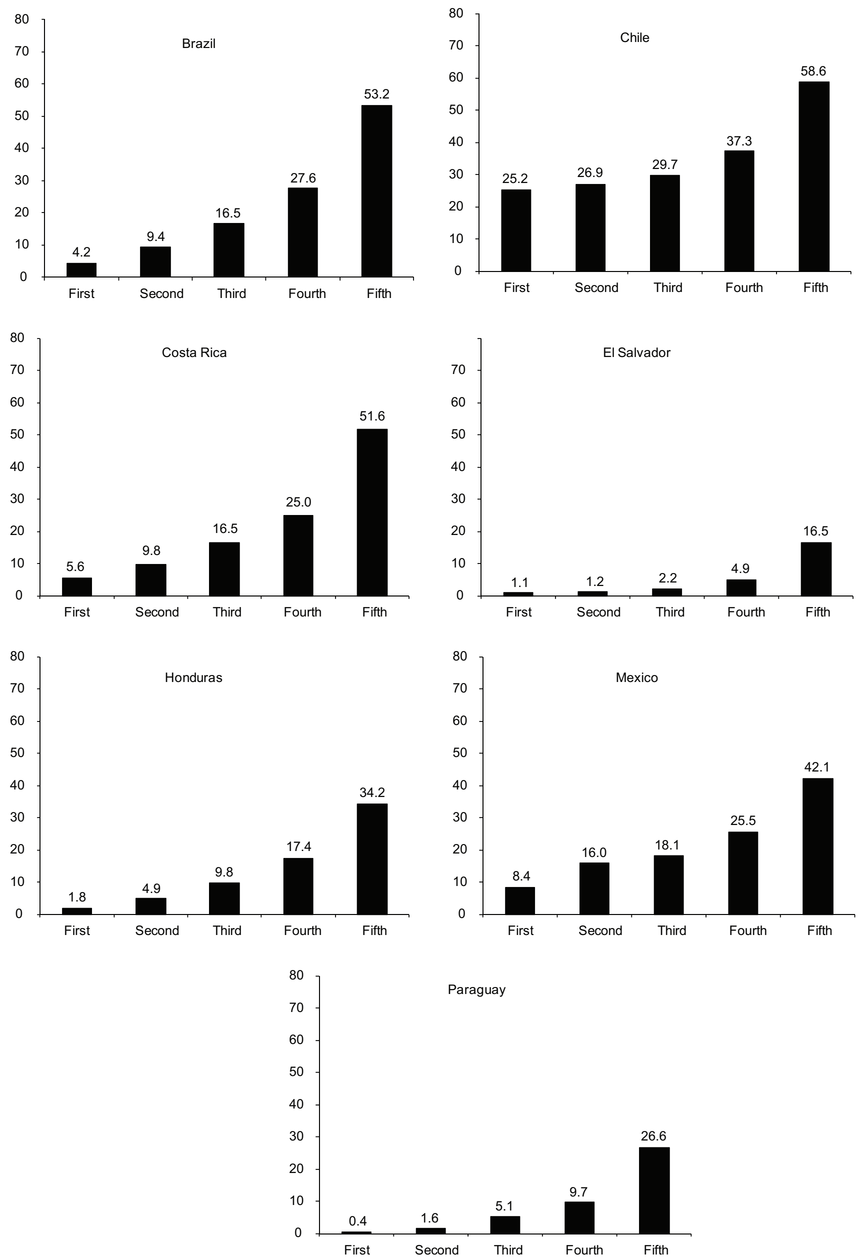
Country	Access/Year	2000	2001	2002	2003	2004	2005	2006
Brazil	Total	.	.	.	.	.	21.0	.
	Urban	.	.	.	.	.	24.5	.
	Rural	.	.	.	.	.	3.4	.
Chile	Total	19.2	.	.	28.5	.	.	37.3
	Urban	21.3	.	.	31.1	.	.	40.3
	Rural	5.9	.	.	10.5	.	.	16.9
Costa Rica	Total	.	.	.	.	.	22.1	.
	Urban	.	.	.	.	.	30.0	.
	Rural	.	.	.	.	.	10.5	.
El Salvador	Total	.	.	.	.	.	.	5.0
	Urban	.	.	.	.	.	.	7.5
	Rural	.	.	.	.	.	.	1.0
Honduras	Total	.	.	.	.	5.7	6.6	11.5
	Urban	.	.	.	.	11.5	12.8	20.4
	Rural	.	.	.	.	0.8	1.4	4.0
Mexico	Total	.	8.0	11.9		14.3	17.9	20.2
	Urban	.	.	.	.	.	21.9	28.5
	Rural	.	.	.	.	.	4.7	13.9
Paraguay	Total	.	.	.	.	.	7.9	8.0
	Urban	.	.	.	.	.	12.5	12.6
	Rural	.	.	.	.	.	1.1	1.2

Source: author's elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/

The Internet diffusion is still concentrated in the richest and most educated segments of the population in the majority of countries. Figure III.2 presents Internet use rates by education quintiles, using the number of educational years. With the exception of Chile, where the distribution is relatively more homogeneous, Internet usage is mainly concentrated in the higher educational quintile of the countries. These facts confirm the hypothesis that technology diffusion is often relatively rapid among elites living in cities, but it takes much longer to spread over the rest of the population (World Bank, 2008).

[4] Chile is the only country where the National Household Survey includes questions on Internet use since 2000.

Figure III.2
Latin America: individual Internet use by education quintiles[a]
(Percentages)



Source: Author's elaboration based on National Household Surveys.
[a] *Correspond to quintiles of the average education years of adults in the household.*

Finally, Table III.3 displays the usage patterns of different Internet applications. When considering the different question structures across national household surveys,[5] the descriptive statistics give interesting insights on the patterns of Internet use. Not surprisingly, countries with higher Internet penetration, and where a better connection quality is available, such as Brazil and Costa Rica, show a more differentiated and advanced use of the Internet. Taking an example of an advanced application, in Brazil and Costa Rica almost 20% of Internet users actually use online banking, while in El Salvador and Honduras use rates are around 2%. It is also interesting to notice how education and communication are the most used applications in almost all countries, especially in those where Internet diffusion is lower. It seems that the Internet is an important device for improving education and communication efficiency in developing countries.

Table III.3

Latin America: individual Internet use by application

(Percentages of Internet users)

Application	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Education	71.7	12.2	62.4	59.2	44.1	35.1	20.7
Communication	68.7	59.5	73.8	16.0	49.1	48.5	60.0
Purchasing	13.7	6.4	7.9	3.1	1.3	3.5	1.3
Banking	19.1	6.4	19.7	2.2	2.1	.	.
Government	27.4	9.4	.	0.4	.	5.1	.
Information	24.5	90.9	74.2	5.0	24.1	56.8	57.3
Entertainment	70.7	52.7	47.6	3.8	15.9	20	14.3

Source: Author's elaboration based on the OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/
Note: Data corresponding to latest available year.

4. Empirical model

In this section we present the empirical model to analyze the determinants and patterns of Internet use in Latin American countries. The decision for an individual to use or not use the Internet is assumed to follow a standard utility maximization framework, where an individual chooses to use the Internet when he derives a positive utility from it, *i.e.* when the benefits associated with its use exceed its costs. More formally, the utility deriving from Internet use ($U_{i,U}$) or not use ($U_{i,N}$) is modeled as a linear function of a vector of socio-economic characteristics of the individual (X_i) and a additive stochastic term representing unobservables and measurement error ($\varepsilon_{i,}$):

[5] In some surveys, there is a yes/no question for each application (Brazil, Costa Rica). In other surveys, it is asked to indicate the most frequent used applications (Chile, Honduras, El Salvador and Paraguay). In Mexico it is required to elect only the two most intensively used applications.

$$U_{i,U} = \alpha_U + X_i \beta_U + \varepsilon_{i,U} \quad (1)$$
$$U_{i,N} = \alpha_N + X_i \beta_N + \varepsilon_{i,N} \quad (2)$$

Consequently, the probability that the *i*th individual will use the Internet is the probability that its utility of using is higher than its utility of not using:

$$\Pr(\textit{Internet Use=1}) = \Pr(U_{i,U} > U_{i,N}) = F[(\alpha_U - \alpha_N) + X_i(\beta_U - \beta_N)] \quad (3)$$

Where F is the cumulative distribution function of the error term ($\varepsilon_{i,U} - \varepsilon_{i,N}$). If we assume that ($\varepsilon_{i,U} - \varepsilon_{i,N}$) is normally distributed, the model can be estimated by Maximum Likelihood Estimation (MLE) with a simple Probit regression. Empirically, we estimate the following equation to model the probability of an individual to use the Internet:

$$\Pr(\textit{Internet Use=1}) = F(\alpha + \beta_0{*}\textit{Income}_h + \beta_1{*}\textit{Education}_i + \beta_2{*}\textit{Age}_i + \beta_3{*}\textit{Female}_i + \beta_4{*}\textit{Rural}_i + \beta_5{*}\textit{Student}_i + \beta_6{*}\textit{Employed}_i + \beta_7{*}\textit{Home}_h) \quad (4)$$

Where *Income* represents the natural logarithm of the per capita equivalent income of the household[6] to which the individual belongs to,[7] *Education* is the number of schooling years he attended[8] and *Age* is the age of the individual. For estimation, we consider only individuals older than 6 years. *Female* and *Rural* are dummy variables taking the value of 1 if the person is respectively a woman and is located in a rural area. *Student* and *Employed* dichotomous variables control for the status of the individual. *Student* takes the value of 1 if the person is enrolled in a formal educational program, while *Employed* is equal to 1 if the person works. Note that the two statuses are not reciprocally exclusive, *i.e.* the same individual can present the value 1 for both the variables. Moreover, in a second specification of the model, we divide the *Employed* variable by work category: *Low Skilled Employed* and *Skilled Employed*. Ths would help us to check their different effect on the Internet diffusion.[9] Finally, we include a dummy variable (*Home*) which takes the value of 1 if the individual lives in a household with an available Internet connection.

6 We consider a measure of household income, instead of individual income, because of two main reasons. First, individual income may be misleading in evaluating the actual amount of available money of a person. For instance, many workers with a positive personal income have more limited means than a student with zero personal income but belonging to a wealth family. Second, data on individual income coming from household surveys are often less precise than household ones, given the fact that there is typically only one respondent to the survey for each household.

7 In order to take into account economies of scale in household consumption and obtain more precise income elasticity, we use an equivalent income measure, which is the total household income divided by the so-called LIS (Luxembourg Income Studies) equivalence scale. It is defined as the square root of the number of household members (Atkinson et al., 1995).

8 In the case of Mexico, because of the unavailability of the number of attended educational years in the survey, we included two dummy variables corresponding to educational attainment of the individual (secondary and tertiary education).

9 A worker is defined as skilled if working in the categories: Legislators, senior officials and managers; Professionals; Technicians and associate professionals; Clerks. The low skilled variable is computed residually. See OSILAC ICT Statistical Information System, http://www.cepal.org/tic/flash/.

This model implicitly assumes that the decision to use the Internet can be modeled independently from access. Demoussis and Giannakopoulos (2006) justify this approach arguing that the intention to use the Internet is not always a condition for Internet access. Indeed, it is possible for an individual to surf the Net by employing a network which has been set up for reasons unrelated to his Internet use decisions. But, at the same time, it is obvious that the possibility of accessing the network is a pre-requisite for using it. In other words, individuals might not use the Net not only because they are not interested on it but also because they have not access to it. However, this model does not allow distinguishing between determinants of Internet use and Internet access. Neglecting this issue may bring to misleading conclusions.

Taking this into consideration, we developed an alternative approach in order to disentangle access and use determinants. Given the fact that evaluating actual Internet accessibility in any location for each individual is an impossible task with the available data, we limit the analysis to the use of Internet given access in the house. Some scholars estimated the probability for an individual of using the Internet at home, conditional to living in a household where Internet connection is available *(e.g.* Ono and Zavodny, 2007). But, it is clear that if we restrict our analysis only to individuals who have home access to the Internet, sample selection bias will be introduced, and the direct estimation of a Probit regression on a non-randomly selected sample may lead to biased estimations (Heckman, 1979). Then, in order to solve the problem of selection bias, we employ the two-stage Heckman correction method. In the first stage we estimate the probability of an individual to live in a household with a computer connected to Internet and we use this estimation to build the inverse Mill's ratio, by using its pseudo-residuals. The second stage is a Probit regression which estimates the probability to use Internet at home, corrected with the inclusion of the inverse Mill's ratio of the first step.

Empirically, the first-step equation models the probability for an individual to live in a household with an available Internet connection:

$$\Pr(\textit{Home Access=1}) = F(\gamma + \delta_0{*}\textit{Income}_h + \delta_1{*}\ \textit{Household Education}_h + \delta_2{*}\textit{Family Size}_h + \delta_3{*}\textit{Economic Activity}_h + \delta_4{*}\textit{Student density}_h + \delta_5{*}\textit{Rural}_h) \qquad (5)$$

The interesting point is that the decision of having or not having an available Internet home connection is a choice regarding the household as a whole, while the decision of using Internet is individual. Therefore, regressors of the first-step equation are variables referred to the household in which a person lives and then common to all household members, instead to be individually idiosyncratic. Besides *Income* and *Rural* variables, which correspond to the variables previously described, the other regressors of the equation include: *Household Education* is household education level measured by the average level of educational years of adults (age ≥18);[10] *Family Size* is the number of members of the households potentially capable to use computers (age ≥ 6); *Economic Activity* is the proportion of active individuals (aged between 15 and 65 years) in the household; and *Student density* is the proportion of students in the household.[11]

The second-step equation is similar to the (4), but in this case the dependent variable becomes the probability for an individual to use Internet in the house. Moreover, the inverse Mill's ratio of the first-step equation (ϕ_i/Φ_i) is added as a regressor for correction purposes and, obviously, the availability of a home-connection is not considered, being a pre-requisite for using the Internet at home. Thus, its empirical specification is:

$$\Pr(\textit{Home Use}=1) = F(\lambda + \mu_0 {*}\textit{Income}_h + \mu_1 {*}\textit{Education}_i + \mu_2 {*}\textit{Age}_i + \mu_3 {*}\textit{Female}_i + \mu_4 {*}\textit{Rural}_i + \mu_5 {*}\textit{Student}_i + \mu_6 {*}\textit{Employed}_i + \zeta(\phi_i / \Phi_i)) \qquad (6)$$

Finally, following Goldfarb and Prince (2008), we extend the analysis to the empirical evaluation of determinants of use of single Internet applications. Additionally, we employ a two-stage Heckman selection model, with a Probit regressions in both stages. But now the first stage evaluates the probability for an individual to be an Internet user, *i.e.* it is constituted by equation (4), while the second one examines whether the person goes on-line for specific purposes (*e.g.* for education). As in the previous exercise, we add to the covariates of this last regression the Heckman correction term.[12]

Our empirical investigation employs data coming from National Household Surveys conducted in seven Latin American Countries in 2005 and 2006: Brazil, Chile, Costa Rica, El Salvador, Honduras, Mexico and Paraguay. All the surveys are representative at the national level and cover a wide range of socio-economic variables at individual and household level, such as income, education, age, occupation, among others. Moreover, they contain questions about ICT diffusion in the society. In particular, they include information not only regarding ICT adoption in the household, but also about single individual use.

Resuming, our empirical analysis consists of three parts. First, we identify determinants of individual unconditional on Internet use. Second, we perform a two-step analysis in order to disentangle the determinants of Internet use and Internet access. The first stage is a Probit estimation of the probability of an individual to live in a household with an available connection; and the second stage is also a Probit estimation that identifies

10 The household education level is represented by an index representing the average educational attainment of adults (age ≥18). The exception is Mexico because of the lack of information concerning educational years of individuals. See Table A.1 in the Appendix for a description of variables.

11 For a discussion on the determinants of household ICT access in Latin America, see Grazzi and Vergara (2010).

12 For identification purposes, it is necessary to include in the first-step equation at least a variable that is correlated with the Internet usage, but not with the specific application usage (Greene, 2003). Our chosen instrument is the availability of home-connection, which is supposed to be a determinant of Internet use, but not of the adoption of a specific Internet application.

home-Internet use determinants for individuals living in connected households. Finally, we examine the correlation between individual socioeconomic characteristics and usage of several Internet applications, conditional on Internet use.

5. Estimation results

This section discusses the estimation results. We start with determinants of unconditional Internet use, then we analyze those of Internet use at home conditional to live in a connected household and finally we consider patterns of specific Internet applications. All regressions are country-specific.

(a) Unconditional Internet use

Table III.4 presents the estimated coefficients of the determinants of unconditional individual use of Internet. In Table III.5 the signs of the coefficients are resumed, while Table III.6 displays marginal effects[13]. As expected, in all the regressions coefficients for income and education are positive and significant while those for age are negative and significant. In other words, older, less educated and poorer individuals are less likely to use Internet in all countries. These findings are in line with those obtained by previous studies on Internet diffusion (*e.g.* Vicente and Lopez, 2006; Ono and Zavodny, 2007). Moreover, in all countries but Honduras, there is statistical evidence at 1% that women are less likely to use the Internet, showing the presence of a persistent digital gender divide in Latin America. Another important divide is the urban-rural one, with individuals living in urban areas much more likely to use the Internet than those living in rural ones. In fact, rural areas are disadvantaged in terms of telecommunication infrastructure and reduced provision of ICT services. Analyzing the marginal effects, we note that Chile is the country with the largest gap, with individuals living in rural households, on average and *ceteris paribus,* 12% less likely to use Internet.

[13] Given the non-linearity of the Probit model, marginal effects are not directly obtainable from estimated coefficients.

Table III.4

Determinants of Internet use: probit estimations

Country Variables	Brazil		Chile		Costa Rica	
	(1)	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*
Household Income	0.361*** (0.00524)	0.328*** (0.00526)	0.310*** (0.0101)	0.272*** (0.0100)	0.362*** (0.0187)	0.332*** (0.0187)
Education	0.185*** (0.00156)	0.163*** (0.00161)	0.170*** (0.00284)	0.145*** (0.00285)	0.212*** (0.00443)	0.189*** (0.00464)
Age	-0.037*** (0.000440)	-0.038*** (0.000455)	-0.035*** (0.000659)	-0.036*** (0.000674)	-0.034*** (0.00132)	-0.034*** (0.00135)
Female	-0.156*** (0.00787)	-0.203*** (0.00803)	-0.066*** (0.0145)	-0.127*** (0.0148)	-0.153*** (0.0253)	-0.174*** (0.0255)
Rural	-0.659*** (0.0159)	-0.606*** (0.0158)	-0.504*** (0.0140)	-0.500*** (0.0140)	-0.362*** (0.0232)	-0.363*** (0.0233)
Student	0.664*** (0.0103)	0.607*** (0.0105)	1.679*** (0.0264)	1.551*** (0.0255)	0.777*** (0.0331)	0.749*** (0.0333)
Employed	0.160*** (0.00895)	.	0.153*** (0.0186)	.	0.100*** (0.0302)	.
Low Skilled Employed	.	-0.110*** (0.00998)	.	-0.071*** (0.0195)	.	-0.119*** (0.0331)
Skilled Employed	.	0.617*** (0.0116)	.	0.608*** (0.0244)	.	0.437*** (0.0390)
Internet at home	1.310*** (0.0110)	1.304*** (0.0114)	1.127*** (0.0208)	1.108*** (0.0212)	0.911*** (0.0408)	0.907*** (0.0415)
Constant	-4.090*** (0.0333)	-3.617*** (0.0337)	-5.427*** (0.119)	-4.586*** (0.119)	-6.230*** (0.220)	-5.633*** (0.221)
Log-Likelihood	-86 944.832	-84 139.964	-69 486.656	-67 608.657	-9 666.088	-9 481.738
Wald Chi² *(Prob> Chi²)*	49 396.86 (0.000)	49 996.17 (0.000)	17 246.87 (0.000)	18 302.12 (0.000)	5 568.56	5 545.78 (0.000)
Pseudo-R²	0.493	0.509	0.505	0.517	0.475	0.485
Observations	332 359	332 314	214 865	214 483	33 085	33 064

Source: Author's own elaboration.

*Note: Estimated coefficients from the Probit regression. Robust standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table III.4 (cont.)

Determinants of Internet use: probit estimations

Country Variables	El Salvador (1)	El Salvador (2)	Honduras (1)	Honduras (2)	Paraguay (1)	Paraguay (2)
Household Income	0.253*** (0.0533)	0.237*** (0.0521)	0.209*** (0.00828)	0.210*** (0.00833)	0.498*** (0.0345)	0.476*** (0.0352)
Education	0.174*** (0.00735)	0.164*** (0.00763)	0.132*** (0.00211)	0.134*** (0.00224)	0.177*** (0.00962)	0.155*** (0.0103)
Age	-0.0192*** (0.00345)	-0.020*** (0.00350)	-0.002*** (0.000670)	-0.002*** (0.000671)	-0.022*** (0.00418)	-0.026*** (0.00447)
Female	-0.119*** (0.0418)	-0.129*** (0.0416)	0.037*** (0.0143)	0.039*** (0.0143)	-0.172*** (0.0517)	-0.190*** (0.0521)
Rural	-0.382*** (0.0515)	-0.370*** (0.0509)	-0.325*** (0.0174)	-0.326*** (0.0174)	-0.799*** (0.0704)	-0.796*** (0.0701)
Student	1.057*** (0.0576)	1.049*** (0.0594)	0.567*** (0.0204)	0.569*** (0.0206)	0.623*** (0.0674)	0.564*** (0.0697)
Employed	-0.011 (0.0513)	.	-0.001 (0.0182)	.	-0.286*** (0.0613)	.
Low Skilled Employed	.	-0.163*** (0.0567)	.	0.0124 (0.0193)	.	-0.494*** (0.0711)
Skilled Employed	.	0.204*** (0.0732)	.	-0.0396 (0.0272)	.	0.102 (0.0822)
Internet at home	1.354*** (0.0901)	1.356*** (0.0912)	0.947*** (0.0411)	0.948*** (0.0411)	0.927*** (0.122)	0.944*** (0.122)
Constant	-4.625*** (0.270)	-4.420*** (0.273)	-3.813*** (0.0691)	-3.834*** (0.0704)	-9.382*** (0.475)	-8.753*** (0.485)
Log-Likelihood	-5 976.375	-5 938.105	-19 191.526	-19 142.515	-2 292.029	-2 249.494
Wald Chi^2 *(Prob> Chi^2)*	1 595.62 (0.000)	1 617.83 (0.000)	10 338.26 (0.000)	10 317.32 (0.000)	1 113.17 (0.000)	1 093.12 (0.000)
Pseudo-R^2	0.435	0.439	0.266	0.266	0.392	0.403
Observations	53 034	53 034	69 349	69 118	12 118	12 118

Source: Author's own elaboration.

*Note: Estimated coefficients from the Probit regression. Robust standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table III.4 (cont.)
Determinants of Internet use: probit estimations

Country Variables	*Mexico* (1)	(2)
Household income	0.317*** (0.0287)	0.276*** (0.0284)
Secondary education	1.034*** (0.0658)	1.034*** (0.0683)
Tertiary Education	1.858*** (0.0825)	1.611*** (0.0902)
Age	-0.031*** (0.00252)	-0.033*** (0.00263)
Female	-0.112** (0.0499)	-0.161*** (0.0523)
Rural	-0.174*** (0.0482)	-0.168*** (0.0496)
Student	1.238*** (0.0704)	1.195*** (0.0694)
Employed	0.238*** (0.0608)	.
Low Skilled Employed	.	-0.0198 (0.0656)
Skilled Employed	.	0.807*** (0.0789)
Internet at home	1.133*** (0.0680)	1.126*** (0.0708)
Constant	-3.909*** (0.252)	-3.443*** (0.248)
Log-Likelihood	-4 506.328	-4 337.523
Wald Chi² *(Prob> Chi²)*	1 664.96 (0.000)	1 640.75 (0.000)
Pseudo-R²	0.426	0.448
Observations	14 991	14 991

Source: Author's own elaboration.
Note: Estimated coefficients from the Probit regression. Robust standard errors in parenthesis,
** Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Student status is also a positive and significant determinant of Internet use in all the considered countries. The positive effect on Internet use of being a student may refer to several different reasons: the possibility to be connected to the Internet in schools, the need for students to use Internet tool in order to comply with homework, the increased utility of using the Internet as a communication channel with connected school-mates, among others. Differences among countries in the size of marginal effects may reflect differences in the diffusion of Internet in the education system in each country. Chile is the country with the highest value (a student has a 58.2% higher probability to be connected to the Internet, on average and *ceteris paribus*, than not students), while El Salvador and Paraguay have the lowest values. This result confirms the role played by schools as a powerful engine of technology diffusion.

Table III.5
Determinants of Internet use: resume

Country	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Variable				*Specification (1)*			
Income	+	+	+	+	+	+	+
Education	+	+	+	+	+	+	+
Age	-	-	-	-	-	-	-
Female	-	-	-	-	+	-	-
Rural	-	-	-	-	-	-	-
Student	+	+	+	+	+	+	+
Employed	+	+	+			+	-
Internet at home	+	+	+	+	+	+	+
				Specification (2)			
Income	+	+	+	+	+	+	+
Education	+	+	+	+	+	+	+
Age	-	-	-	-	-	-	-
Female	-	-	-	-	+	-	-
Rural	-	-	-	-	-	-	-
Student	+	+	+	+	+	+	+
Low skilled employed	-	-	-	-			-
Skilled employed	+	+	+	+		+	
Internet at home	+	+	+	+	+	+	+

Source: Author's elaboration based on Probit estimations for each country.

About employment status, our empirical analysis shows mixed results: in Brazil, Chile, Costa Rica and Mexico the estimated coefficients are positive and significant, in Paraguay it is negative and significant, and in El Salvador and Honduras they are not statistically significant. The hypothesis is that the variable captures two opposite effects: a positive one, which corresponds to people using Internet for job-purposes or more conscious of Internet utility because of their interaction with people using it, but also a negative one, given by people not using Internet at work and with less free-time or interest to connect to Internet out of working hours. In order to test this hypothesis, we have divided employed individuals in those who are supposed to use Internet at work with higher probability (*Skilled Employed*) and those who are supposed to use it with lower probability (*Low Skilled Employed*). Results are shown in Column (2) of each table. On one hand, as expected, coefficients of *Skilled Employed* remain positive and significant in those countries where the variable *Employed* was positive and significant, but with much higher marginal effects. Additionally, the coefficient for El Salvador becomes positive and significant at 1%, while coefficients for Paraguay and Honduras are not significant. On the other hand, coefficients for low skilled workers are negative and significant at 1%, except for Mexico and Honduras where they are not significant. These results suggest that workplace is an important driver of technology diffusion, but only when the technology is directly adopted by workers.

Table III.6

Determinants of Internet use: probit estimations, marginal effects

Country / Variables	Brazil (1)	Brazil (2)	Chile (1)	Chile (2)	Costa Rica (1)	Costa Rica (2)
Household Income$_i$	0.043*** (0.00524)	0.038*** (0.00526)	0.093*** (0.0101)	0.082*** (0.0100)	0.060*** (0.0187)	0.055*** (0.0187)
Education$_i$	0.022*** (0.00156)	0.019*** (0.00161)	0.051*** (0.00284)	0.044*** (0.00285)	0.035*** (0.00443)	0.032*** (0.00464)
Age$_i$	-0.004*** (0.000440)	-0.004*** (0.000455)	-0.011*** (0.000659)	-0.011*** (0.000674)	-0.006*** (0.00132)	-0.006*** (0.00135)
Female$_i$	-0.019*** (0.00787)	-0.024*** (0.00803)	-0.020*** (0.0145)	-0.038*** (0.0148)	-0.025*** (0.0253)	-0.029*** (0.0255)
Rural$_i$	-0.056*** (0.0159)	-0.052*** (0.0158)	-0.128*** (0.0140)	-0.129*** (0.0140)	-0.057*** (0.0232)	-0.058*** (0.0233)
Student$_i$	0.102*** (0.0103)	0.090*** (0.0105)	0.582*** (0.0264)	0.543*** (0.0255)	0.165*** (0.0331)	0.159*** (0.0333)
Employed$_i$	0.019*** (0.00895)	.	0.046*** (0.0186)	.	0.017*** (0.0302)	.
Low skilled employed	.	-0.013*** (0.00998)	.	-0.021*** (0.0195)	.	-0.019*** (0.0331)
Skilled employed	.	0.100*** (0.0116)	.	0.208*** (0.0244)	.	0.088*** (0.0390)
Internet at home	0.289*** (0.0110)	0.286*** (0.0114)	0.394*** (0.0208)	0.389*** (0.0212)	0.226*** (0.0408)	0.226*** (0.0415)
Log-Likelihood	-86 944.832	-84 139.964	-69 486.656	-67 608.657	-9 666.088	-9 481.738
Observations	332 359	332 314	214 865	214 483	33 085	33 064

Country / Variables	El Salvador (1)	El Salvador (2)	Honduras (1)	Honduras (2)	Paraguay (1)	Paraguay (2)
Household income$_i$	0.002*** (0.0533)	0.002*** (0.0521)	0.029*** (0.00828)	0.029*** (0.00833)	0.018*** (0.0345)	0.016*** (0.0352)
Education$_i$	0.001*** (0.00735)	0.001*** (0.00763)	0.018*** (0.00211)	0.019*** (0.00224)	0.006*** (0.00962)	0.005*** (0.0103)
Age$_i$	-0.001*** (0.00345)	-0.001*** (0.00350)	-0.001*** (0.00067)	-0.001*** (0.000671)	-0.001*** (0.00418)	-0.001*** (0.00447)
Female$_i$	-0.001*** (0.0418)	-0.001*** (0.0416)	0.005*** (0.0143)	0.005*** (0.0143)	-0.006*** (0.0517)	-0.007*** (0.0521)
Rural$_i$	-0.003*** (0.0515)	-0.003*** (0.0509)	-0.046*** (0.0174)	-0.046*** (0.0174)	-0.027*** (0.0704)	-0.025*** (0.0701)
Student$_i$	0.022*** (0.0576)	0.021*** (0.0594)	0.087*** (0.0204)	0.087*** (0.0206)	0.029*** (0.0674)	0.024*** (0.0697)
Employed$_i$	-0.001 (0.0513)	.	-0.001 (0.0182)	.	-0.011*** (0.0613)	.
Low skilled employed	.	-0.001*** (0.0567)	.	0.002 (0.0193)	.	-0.017*** (0.0711)
Skilled employed	.	0.002*** (0.0732)	.	-0.005 (0.0272)	.	0.004 (0.0822)
Internet at home	0.069*** (0.0901)	0.068*** (0.0912)	0.231*** (0.0411)	0.231*** (0.0411)	0.086*** (0.122)	0.086*** (0.122)
Log-Likelihood	-5 976.375	-5 938.105	-19 191.526	-19 142.515	-2 292.029	-2 249.494
Observations	53 034	53 034	69 349	69 118	12 118	12 118

Source: Author's own elaboration.

*Note: Shown are the marginal effects of the estimated coefficients from Probit regression. Robust standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table III.6 (*cont.*)

Determinants of Internet use: probit estimations, marginal effects

Country	*Mexico*	
Variables	*(1)*	*(2)*
Household income	0.047***	0.038***
	(0.0287)	(0.0284)
Secondary education	0.183***	0.172***
	(0.0658)	(0.0683)
Tertiary education	0.508***	0.407***
	(0.0825)	(0.0902)
Age	-0.005***	-0.005***
	(0.00252)	(0.00263)
Female	-0.017**	-0.022***
	(0.0499)	(0.0523)
Rural	-0.026***	-0.024***
	(0.0482)	(0.0496)
Student	0.291***	0.263***
	(0.0704)	(0.0694)
Employed	0.034***	.
	(0.0608)	
Low skilled employed	.	-0.003
		(0.0656)
Skilled employed	.	0.166***
		(0.0789)
Internet at home	0.285***	0.269***
	(0.0680)	(0.0708)
Log-Likelihood	-4 506.328	-4 337.523
Observations	14 991	14 991

Source: Author's own elaboration.
Note: Shown are the marginal effects of the estimated coefficients from Probit regression.
*Coefficient robust standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Finally, it is interesting to notice that the coefficients associated with living in a household with an available Internet connection are positive and significant at 1% in all the considered countries. Even if we are aware that a large part of these results could be due to the fact that people using Internet are more interested in having home connection than people not using it, the magnitude of the marginal effects seems to confirm the idea that access to Internet remains a major issue in Latin America. In other words, when a person has an available connection at disposal, his probability of using the Internet is considerably higher.

(b) Home Internet use

Table III.7 contains the estimations results of the determinants of Internet use at home correcting for sample selection.[14] Table III.8 resumes these results and Table III.9 shows the related marginal effects. We start the analysis with those variables which are common to all members of the household. *Income* remains an important determinant in all the countries

[14] In 5 Countries (Brazil, Chile, El Salvador, Honduras and Mexico) there is evidence of sample selection, while in Costa Rica and Paraguay there is not such evidence. However, results obtained by simple Probit estimations of Internet use at home for these countries do not vary substantially from those displayed here.

except El Salvador. It means that, provided the availability of Internet in the house, individuals living in a richer household present higher probability to use that connection. In fact, households with higher income can afford both a better quality of connection and a longer connection time if compared with poorer ones. And it clearly improves the penetration of Internet use in the whole household. Moreover, a higher income could also mean more connected computers in the household, making actual access to the Internet easier. About location, the coefficients of the *Rural* variable are negative and significant in the majority of the countries, reflecting poorer quality and higher prices of telecommunication services in rural areas.

Table III.7

Determinants of Internet home-availability and Internet use at home: bivariate probit estimations with sample selection

Country	***Brazil***		***Chile***		**Costa Rica**	
Variables	Internet at home (1)	Internet use at home (2)	Internet at home (1)	Internet use at home (2)	Internet at home (1)	Internet use at home (2)
Household income	0.693*** (0.0059)	0.259*** (0.0194)	0.598*** (0.022)	0.198*** (0.030)	0.576*** (0.025)	0.239*** (0.070)
Household education	0.164*** (0.0016)	.	0.146*** (0.0036)	.	0.175*** (0.006)	.
Family size	0.072*** (0.0025)	.	0.002 (0.0043)	.	0.085*** (0.009)	.
Household economic activity	0.483*** (0.0123)	.	0.570*** (0.0216)	.	0.440*** (0.043)	.
Student density	. 0.793*** (0.0176)	.	1.318*** (0.0368)	.	0.330*** (0.062)	.
Rural	-0.681*** (0.0267)	-0.186*** (0.0724)	-0.713*** (0.0191)	-0.538*** (0.059)	-0.180*** (0.028)	-0.190*** (0.070)
Female	.	-0.301*** (0.0177)	.	-0.161*** (0.029)	.	-0.200*** (0.064)
Age	.	-0.043*** (0.0007)	.	-0.027*** (0.001)	.	0.023*** (0.002)
Education	.	0.184*** (0.0029)	.	0.101*** (0.006)	.	0.164*** (0.010)
Student	.	0.717*** (0.030)	.	0.489*** (0.055)	.	0.703*** (0.098)
Employed	.	0.078*** (0.0201)	.	-0.092** (0.036)	.	-0.093 (0.077)
Constant	-8.077*** (0.0421)	-1.992*** (0.1874)	-10.766*** (0.1419)	-2.219 (0.456)	-10.847*** (0.290)	-3.848*** (1.015)
Log-Likelihood	-45 100 000		-5 871 805		-.940 742.5	
$\rho = Cov(\varepsilon_1, \varepsilon_2)$	0.227		-0.139		0.129	
Atanh $\rho = \frac{1}{2} \ln(1+\rho/1-\rho)$	0.231*** (0.033)		-0.140*** (0.009)		0.130 (0.101)	
Wald Chi^2 *(7)* *(Prob> Chi^2)*	8 824.18 (0.000)		1 641.89 (0.000)		539.46 (0.000)	
Wald Test of indep. eqs. (ρ =0) Chi^2 *(1)* *(Prob> Chi^2)*	47.73 (0.000)		6.83 (0.009)		1.65 (0.198)	
Uncensored observations	45 746		21 552		2,677	
Censored observations	315 631		220 343		35 613	
Total observations	361 377		241 895		38 290	

Source: Author's own elaboration.

*Note: Standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table III.7 (*cont.*)

Determinants of Internet home-availability and Internet use at home: bivariate probit estimations with sample selection

Country	El Salvador		Honduras		Paraguay	
Variables	Internet at home (1)	Internet use at home (2)	Internet at home (1)	Internet use at home (2)	Internet at home (1)	Internet use at home (2)
Household income	0.486*** (0.048)	-0.151 (0.114)	0.415*** (0.022)	0.268*** (0.059)	0.645*** (0.054)	0.155 (0.249)
Household education	0.198*** (0.014)	.	0.206*** (0.006)	.	0.117*** (0.014)	.
Family size	0.054*** (0.020)	.	0.046*** (0.007)	.	0.008 (0.018)	.
Household economic activity	0.467*** (0.087)	.	0.219*** (0.044)	.	0.196* (0.102)	.
Student density	0.278** (0.128)	.	0.244*** (0.064)	.	0.091 (0.154)	.
Rural	-0.662*** (0.093)	0.017 (0.312)	-0.535*** (0.079)	-0.509** (0.229)	-0.661*** (0.192)	0.258 (0.887)
Female	.	-0.163 (0.136)	.	-0.197*** (0.077)	.	-0.400** (0.044)
Age	.	-0.012* (0.006)	.	0.021*** (0.003)	.	-0.025** (0.012)
Education	.	-0.047** (0.021)	.	0.158*** (0.010)	.	0.201*** (0.031)
Student	.	0.491** (0.236)	.	0.550*** (0.129)	.	0.379 (0.263)
Employed	.	-0.043 (0.179)	.	-0.274*** (0.099)	.	-0.850*** (0.139)
Constant	-7.478*** (0.318)	1.108 (1.106)	-8.101*** (0.192)	-3.606*** (0.705)	-12.832*** (0.736)	-4.140 (4.197)
Log-Likelihood	-434 724		-295 762		-255 048.3	
ρ = *Cov*(ε_1, ε_2)	-0.338		-0.295		0.463	
Atanh ρ = ½ *ln*(1+ρ/1-ρ)	0.352* (0.193)		0.304*** (0.104)		0.502 (0.372)	
Wald Chi^2 *(7)* *(Prob> Chi*^{2}*)*	36.68 (0.000)		297.21 (0.000)		151.69 (0.000)	
Wald Test of indep. eqs. (ρ =0) *Chi*^{2} *(1)* *(Prob> Chi*^{2}*)*	3.32 (0.068)		8.61 (0.003)		1.82 (0.178)	
Uncensored observations	846		1 396		255	
Censored observations	59 127		80 813		16 661	
Total observations	59 973		82 209		16 916	

Source: Author's own elaboration.
*Note: Standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table III.7 (*cont.*)

Determinants of Internet home-availability and Internet use at home: bivariate probit estimations with sample selection

Country	***Mexico***	
Variables	Internet at home (1)	Internet use at home (2)
Household income	0.273*** (0.034)	0.230*** (0.061)
Household education	3.898*** (0.169)	.
Family size	0.131*** (0.012)	.
Household economic activity	0.766*** (0.080)	.
Student density	-0.713*** (0.115)	.
Rural	-0.357*** (0.054)	0.043 (0.146)
Female	.	-0.324*** (0.116)
Age	.	-0.039*** (0.005)
Secondary education	.	1.088*** (0.227)
Tertiary education	.	1.561*** (0.252)
Student	.	0.707*** (0.178)
Employed	.	0.091 (0.139)
Constant	-7.182*** (0.313)	-2.055*** (0.701)
Log-Likelihood	-18 700 000	
ρ = *Cov*($\varepsilon_{1,}$ ε_2)	0.337	
Atanh ρ = *½ ln(1+*ρ*/1-*ρ*)*	0.351*** (0.135)	
Wald Chi² (8) *(Prob> Chi²)*	211.09 (0.000)	
Wald Test of indep. eqs. (ρ *=0) Chi² (1) (Prob> Chi²)*	6.73 (0.009)	
Uncensored observations	1 573	
Censored observations	15 785	
Total observations	17 358	

Source: Author's own elaboration.
*Note: Standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table III.8
Determinants of Internet use at home: resume

Country Variable	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Income	+	+	+		+	+	
Education	+	+	+	+	+	+	+
Age	-	-	-	-	-	-	-
Female	-	-	-		-	-	-
Rural	-	-	-		-		
Student	+	+	+	+	+	+	
Employed	+	-			-		-

Source: Author's elaboration based on HeckProbit estimations for each country.

Shifting the attention to individual-specific variables, we are able to evaluate drivers of intra-household technology diffusion. As expected, education is the main driver of the Internet use conditional on access, being positive and significant in all regressions. Also the student condition dummy is positive and significant, except in the case of Paraguay. It shows the importance of the contribution of schools to technology diffusion not only as a mere access point. Additionally, it is important to notice the statistical evidence of an age and gender gap in the households (except for El Salvador where the coefficient of the *Female* dummy is not significant). It means that young people and males are more likely to use the Internet than older and females, even when access is provided. Analyzing marginal effects, it is possible to notice that even in those countries with better economic conditions and broader technology diffusion, the Internet gender gap remains strong. Given Internet access at home, women are, on average and *ceteris paribus* 10.4% less likely to use Internet at home in Brazil, 10.0% less in Mexico, 6.7% less in Costa Rica, 6.4% less in Chile. With regard to the existence of such gender gap, a possible explanation could refer to women's role in Latin American societies. Several social studies evaluating work division between genders in Latin America attribute to women activities of *reproductive labor* and *care economy.*[15] Moreover, researches based on regional time-use surveys found that Latin American women work less paid hours than men, but that their total amount of working hours is higher (*e.g.* Milosavljevic, 2007). Then, women of the region have less available free time than men and it may explain some of the differences in Internet use.

15 The concept of *Reproductive labor* refers to the unpaid work that is necessary to ensure the daily maintenance and ongoing reproduction for the labor force, while care economy implies physical or emotional care of any household member, independently from his belonging to household labor force (Mignon, 2005)

Table III.9

Determinants of Internet use at home: heck probit estimations, marginal effects

Country variables	*Brazil*	*Chile*	*Costa Rica*	*El Salvador*	*Honduras*	*Mexico*	Paraguay
Income$_i$	0.090*** (0.0194)	0.079*** (0.0296)	0.081*** (0.0700)	-0.058 (0.1143)	0.029*** (0.0588)	0.071*** (0.0613)	0.051 (0.0249)
Education$_i$	0.064*** (0.0029)	0.040*** (0.0055)	0.055*** (0.0099)	0.018** (0.0211)	0.017*** (0.0104)	.	0.067*** (0.0307)
Secondary Education	.	.	.	.	.	0.360*** (0.2265)	.
Tertiary Education	.	.	.	.	.	0.557*** (0.2516)	.
Age$_i$	-0.015*** (0.0008)	-0.011*** (0.0012)	-0.008*** (0.0025)	-0.005* (0.0064)	-0.002*** (0.0035)	-0.012*** (0.0049)	-0.008** (0.0123)
Female$_i$	-0.104*** (0.0178)	-0.064*** (0.0295)	-0.067*** (0.0644)	-0.062 (0.1355)	0.022*** (0.0765)	-0.100** (0.1165)	-0.132** (0.1985)
Rural$_i$	-0.062*** (0.0724)	-0.211*** (0.0590)	-0.063*** (0.0695)	0.006 (0.3124)	-0.058** (0.2293)	0.013 (0.1457)	0.124 (0.8875)
Student$_i$	0.248*** (0.0304)	0.194*** (0.0552)	0.237*** (0.0977)	0.180** (0.2356)	0.069*** (0.1288)	0.235*** (0.1780)	0.029 (0.2634)
Employed$_i$	0.027*** (0.0202)	-0.036*** (0.0361)	-0.031 (0.0769)	-0.016 (0.1786)	-0.030 (0.0987)	0.028 (0.1385)	-0.282** (0.2506)
Uncensored Observations	45 746	21 552	2 667	846	1 369	1 573	255

Source: Author's own elaboration.
*Note: Shown are the marginal effects of the estimated coefficients from HeckProbit regression. Robust standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

(c) Use of different Internet applications

Finally, Table III.10 resumes estimation results of the determinants of single Internet applications, obtained by performing separate *HeckProbit* estimations for each available application in each country. Even though some caution is needed given the different format of the question in different countries (see Section 3), some relevant conclusions can be drawn.

First, not surprisingly, individual education level influences positively the probability to use the most sophisticated applications, such as banking, purchasing and government. It confirms the fact that some technological skills are necessary to fully exploit Internet potentialities. Second, being a woman has a positive effect on the probability of using the Internet for activities related to education and training, while it has a negative effect on entertainment, banking and purchasing activities. The gender wage differential and the high percentage of women without own resources in Latin America[16] may explain the negative coefficients associated to Internet purchasing and banking, while the lack of free time is related to less Internet use for entertainment activities.[17] For similar reasons, employment status has a negative and significant effect on Internet use for entertainment in four of the considered countries (Brazil, Chile, Costa Rica and El Salvador): individuals with a formal job have, on average, less free time to dedicate to entertainment. Third, individuals located in rural areas are more likely to use the Internet tool for education purposes, confirming the potential impact of connectivity for improving rural human capital. In fact, Internet diffusion can constitute an important help in overcoming barriers to education deriving from physical infrastructure limitations in rural areas.

Table III.10

Determinants of Internet application use: resume table

Education

Country Variable	**Brazil**	**Chile**	**Costa Rica**	**El Salvador**	**Honduras**	**Mexico**	**Paraguay**
Income	+	+			-	-	
Education	+	+			-		-
Age	-	+	-		-		-
Female	+		+	+	-	+	
Rural	+	+		+	+		+
Student	+	+	+	+	+	+	+
Employed	-	+	-	-	-	-	

Communication

Country Variable	**Brazil**	**Chile**	**Costa Rica**	**El Salvador**	**Honduras**	**Mexico**	**Paraguay**
Income	+	+	+		+	+	
Education	+	+	+	-			
Age	-	-					
Female		+			+	+	+
Rural	-	-				+	
Student	-		-	-	-	-	-
Employed		+	+	-	-		+

Purchasing

Country Variable	**Brazil**	**Chile**	**Costa Rica**	**El Salvador**	**Honduras**	**Mexico**	**Paraguay**
Income	+	+	+			*	
Education	+	+		+		*	-
Age	+	+	+			*	+
Female	-	-	-		-	*	-
Rural	+			-		*	-
Student	-	-	-	-	-	*	
Employed	+	+	+	+	+	*	

[16] In Mexico and Chile, for example, 45% of women are without own resources (Montaño, 2009).

[17] For an overview of the gender differences in Internet use in OECD and some non-OECD countries, see OECD (2008) and Montagnier and Van Welsum (2006).

Table III.10 (*cont.*)

Determinants of Internet application use: resume table

Banking

Country Variable	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Income	+	+	+	-	*	*	*
Education	+	+			*	*	*
Age	+	+	+		*	*	*
Female	-	-			*	*	*
Rural			+	+	*	*	*
Student	-	-	-	-	*	*	*
Employed	+	+	+	-	*	*	*

Government

Country Variable	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Income	+	+	*	*	*		*
Education	+	+	*	*	*		*
Age	+	+	*	*	*	+	*
Female	-		*	*	*		*
Rural	-	-	*	*	*	-	*
Student	-	-	*	*	*		*
Employed	+	+	*	*	*	+	*

Information

Country Variable	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Income	-	-	+		-		
Education	+		+			+	
Age	-	+			-	+	+
Female	+				-		
Rural	-	+	+		+		+
Student	-	+	-	-	-		
Employed	+	+	+	+	+		+

Entertainment

Country Variable	Brazil	Chile	Costa Rica	El Salvador	Honduras	Mexico	Paraguay
Income	+	+	+				-
Education				-	-	-	-
Age	-	-	-		-	-	-
Female	-	-	-	-	-	-	-
Rural		-	-				+
Student	-	-	-	-	-	-	-
Employed	-	-	-	-			

Source: Author's elaboration.

6. Concluding remarks

The role played by Internet in modern societies is becoming increasingly important. Early visions were generally optimistic in considering it as an equalizing factor both at international and at domestic level, but successive scholars have highlighted the risk that the dynamics of its diffusion process could advantage those who were yet advantaged in terms of economic resources and social status, and, consequently worsen pre-existing inequalities rather than ameliorate it.

This paper contributes to understanding this issue by performing three different econometric exercises, whose results clarify the determinants and patterns of Internet use in Latin America. First, the importance of the traditional determinants, such as income, age and education is confirmed by the analysis of unconditional Internet use. Moreover, there is evidence of both an urban/rural and a gender divide in almost all the considered countries. Second, we decoupled determinants of Internet use from those of access, finding that access does not translate automatically into usage. In other words, even when access to the Internet is provided, differences in actual use decrease but remain. In particular, females are found to be less likely to use Internet, even once access is provided. This finding shows how the total gender divide could be divided in two different components: an *access divide* and a *use divide*. Granting access does not necessarily mean to erase the whole gender digital divide. Finally, the analysis of single Internet application use gives some evidence of a differentiated use by socio-demographic categories, suggesting that women and people located in rural areas could benefit relatively more from Internet diffusion.

The findings of this work uncover some of the characteristics of the Internet diffusion process, which is a key aspect for the full understanding of the phenomenon and for the designing of effective policies directed to close the existing digital divides in the region.

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8. Appendix

Table A.1
Description of Variables

Variable	*Description*
Pr(Internet Use=1)	Internet Use. 1:yes; 0: no.
Pr(Home Use=1)	Internet Use at home. 1:yes; 0: no.
Pr(Education=1)	Internet Use for education. 1:yes; 0: no.
Pr(Communication=1)	Internet Use for communication. 1:yes; 0: no.
Pr(Purchasing=1)	Internet Use for purchasing. 1:yes; 0: no.
Pr(Banking=1)	Internet Use for banking. 1:yes; 0: no.
Pr(Government=1)	Internet Use for government. 1:yes; 0: no.
Pr(Information=1)	Internet Use for information. 1:yes; 0: no.
Pr(Entertainment=1)	Internet Use for entertainment. 1:yes; 0: no.
$Income_h$	Log_n of equivalent household income.
$Education_i$	Number of education years.
Age_i	Years of age.
$Female_i$	Gender. 1: female; 0: male.
Rural	Location. 1: rural; 0: urban.
$Student_i$	Student Condition. 1:yes; 0:no.
Employed	Employed Condition. 1:yes; 0:no.
Skilled Employed	Skilled Employed. 1: yes; 0: no.
Low Skilled Employed	Low Skilled Employed. 1: yes; 0: no.
Household Education $_h$	Average of adults education years (age≥18).
Family Size$_h$	Number of family members (age≥6).
Economic Activity$_h$	Proportion of economic active members in the household (16≤age≤65).
Student Density$_h$	Proportion of students in the household.

Source: Author’s elaboration.

III. Impact of Internet use on individual earnings

Lucas Navarro[1]

1. Introduction

It is widely accepted that the diffusion of Information and Communication Technologies (ICT) is an important determinant of growth and development. In this context, the emergence of the Internet as a means for information exchange has motivated an increasing literature on its benefits. The potential benefits start with the productivity enhancing effect of computer and Internet use at the workplace firstly explored by Krueger (1993). Among other impacts, the possibility of working from home and trading on the Internet could have significant effects on the efficiency of use of time (Douma *et al*., 2003; Sinai and Waldfogel, 2003; Goolsbee and Klenow, 2006). For job seekers, search on the Internet could help to improve the efficiency of the firms-workers matching process (Kuhn and Skuterud, 2004; Stevenson, 2009). Internet access related to e-learning can also be a means for children to perform better at school.[2] Also, a lot of procedures for firms and citizens can be simplified due to the Internet.

Despite of the benefits of ICT dissemination, there has been increasing concern in industrialized economies about the "*digital divide*", understood as the gap between those who access and use the ICT and those who do not. Presumably, this concern is founded on the premises that if there are gains from the ICT revolution, they are enjoyed only by those who use the new technologies. If that is the case, the digital divide could be a potentially dangerous driver of increased inequality. The evidence on the effects of the digital divide on earnings inequality is scarce and mixed. Borghans and Weel (2007, 2008) and Forman *et al*. (2009) analyze the impact of the speed and rate of computer diffusion on the wage structure. These studies do not find a sizeable effect of the digital divide on wage inequality in developed countries. On the other hand, using data for five European countries, Haisken-DeNew and D'Ambrosio (2003) analyze the impact of ICT on the distribution of wages and they find a positive impact of not using Internet at work on the risk of social exclusion. This effect is related to the Internet and PC usage wage premium in the workplace.

1 The author thanks Cesar Cristancho for statistical assistance and Matteo Grazzi, Miguel Torres, Sebastián Vergara and Manuel Willington for very helpful conversations. Usual disclaimers apply.

2 Fairlie (2005), Beltran *et al.* (2009) and Fairlie and London (2009) analyze the impact of computer use on educational outcomes.

Where can we place the developing world, and in particular Latin America, in this context? First, there is no reason to expect that the diffusion of new ICT could not be beneficial for the region.[3] Second, the profound inequality in income and access to education and public services in general is reflected in a high inequality of computer and Internet access as reported by Grazzi and Vergara (2010). Third, if there is a return to use of ICT, the digital divide could be a dramatic source of greater inequality. Moreover, in the case of Latin America we can think of a "*social divide"* that precedes and is more important than the digital divide. The digital divide may be then another reflection of the social divide that would persist as long as the problems of high poverty levels and unequal access to quality education were not tackled. This is probably why, as stated in Adeya (2002) and APDIP (2005), some studies cannot find a solid link between ICT and poverty reduction. In a similar vein, they are not clear on which ICT are relevant under which circumstances.

An implication of these effects is that the greater the impact of Internet use, the more severe the harmful effects of the digital divide. Measuring the impact of ICT is essential in order to evaluate to what extent the digital divide imposes serious limits to economic opportunities for the excluded. In this respect, the literature on the impact of ICT in Latin America is still in its infancy. In an attempt to fill this gap, this study uses matching techniques to investigate the impact of Internet use on individual earnings in six countries of the region. The analysis is performed using recent National Household Survey data for Brazil, Chile, Costa Rica, Honduras, Mexico and Paraguay.

There is extensive literature on the effects of human capital on productivity and economic growth. If the Internet is a source of knowledge, its effective use can be thought of as a channel for productivity and earning increases. Therefore, it would be expected that those who use the Internet may have an earning advantage over the non users. Testing this hypothesis, however, is problematic because of a double causality issue. The high positive correlation between Internet use and income reflects not only that accessing the web can have an impact on income but also that the prevalence of Internet use is greater among the wealthiest segment of the population. In panel-data studies this is not a major problem given that it is possible to track individuals' earnings before and after the Internet adoption. Although this is not an option in this study, the use of matching techniques would help to reduce the selection problem. If the question is how Internet users would perform if they were not using the Internet, it is necessary to construct a counterfactual. This is done by identifying groups of treated (Internet users) and controls (non-users) with similar characteristics. These include education, sector of activity, occupation, age and other variables that approximate their wealth before Internet adoption. Subsequently, the treated and control groups are matched according to the nearest neighbor method. Finally, average earnings differential between the two groups are computed, which is the measure of the return to Internet use obtained in this study.

[3] According to Peres and Hilbert (2009), despite the rates of computer and Internet use in Latin America are converging to the world average, there is a persistent negative gap in the rates of broadband Internet diffusion.

To implement the empirical strategy, the sample is divided in two groups: Salaried and Self-employed workers. The data for the countries analyzed show clear differences between them in the patterns of Internet use. Indeed, while salaried workers mainly access the Internet at work, the self-employed typically use the Internet at home and at other common access places. There are implications related to Internet adoption associated to this differential behavior. Usually, the decision to adopt Internet at work is made by the employer. This has motivated a literature on the returns to computers and Internet use at the workplace on earnings. Therefore, the impact of Internet use would be related to both firms' and workers' characteristics. In contrast, the self-employed make their adoption decision on their own and incur the corresponding costs. In this case, the returns to use would be explained only by worker characteristics. Also, since most of the Internet use for this group is at home, the analysis can better grasp the impact of home access.

The study is organized as follows. The next section discusses the theoretical motivations and the literature on the impact of the ICT of interest on earnings. Section 3 presents the empirical approach followed to tackle the research question. Sections 4 and 5 are devoted to the description of the data and the results, respectively. Finally, Section 6 concludes.

2. Literature

Most of the literature on the impact of ICT on earnings relates to the return to computer use at the workplace. If computers increase labor productivity, workers may ultimately benefit with corresponding higher wages. The empirical studies in this literature rely on cross-section and longitudinal data. The interpretation of the PC use premium as a return to computer use based on results from cross-section data may be difficult for many reasons. It could be the case that computer users were already earning higher wages than non users before computers were adopted. Second, firms adopting new ICT may have been paying higher wages earlier on. Then a worker in a firm that uses ICT would earn more than a worker in a firm with no ICT access before and after adoption. Third, the PC wage premium could reflect a change in the relative demand for skills (skilled biased technical change). Alternatively, the adoption decision can be related to the preexistent supply of human capital (Doms and Lewis, 2006). Finally, it would still be difficult to control for the effect of unobserved skills on the PC wage premium (Krueger, 1993; DiNardo and Pischke, 1997).

Based on cross sectional data for the US, Goss and Phillips (2002), Freeman (2002) and Mossberger *et al.* (2006) estimate the impact of Internet use. They use data from different waves of the Current Population Survey (CPS) in the last decade to measure the salaried wage-premium associated to Internet use. Their estimated returns are in the very close range of 13.5-17%. Among the few studies on the return to computer use in Latin

American is the work by Benavente *et al.* (2009) for Chile. Using cross-sectional data for 2000 and 2006, they address the selection problem into computer use by implementing matching techniques. The authors claim that if ICT adoption by firms is independent of the distribution of workers' skills, it would be less likely that their estimations of return to PC use incur an ability bias. Their estimated returns are in the range 15-45% depending on the matching method and year considered.

Panel-data studies can help to identify unobserved constant worker characteristics using fixed-effects. Using longitudinal information for Ecuador, Oosterbek and Ponce (2009) find evidence of a computer use premium at work mainly explained by unobserved worker/job characteristics rather than by a causal effect of computer use on productivity. These results are in line with the findings of Entorf and Kramarz (1997) for France and Haisken-De New and Schmidt (1999) for Germany using panel-data. One problem with panel-data studies is that unobservable worker characteristics could change over time. In addition to that, Pabilonia and Zoghi (2005) suggest that the results of previous studies rely on year-to-year changes in computer use, a period of time in which "workers may be bearing the burden of training costs". Therefore, fixed-effects estimates of returns to computer use may be biased downwards. On the other hand, OLS estimates may be biased upwards if skilled workers are selected into computer use. They therefore propose as an instrument for computer use a dummy for the implementation of a new process in production or the improvement of an existing one with a one-year lag. Their results indicate a zero effect of computer use on wages, after controlling for selection into computer use. Rather than a return to use independent of skill, they also observe a positive return to computer skills (approximated by computer experience).

In a recent work, Dostie *et al.* (2009) use matched employer-employee panel-data for Canada for the period 1999-2002. They find a positive return to computer use even after controlling for the selection problem and unobserved workplace and workers characteristics. Interestingly, the authors find that correcting for workplace effects reduces the observed computer wage premium by half. Based on data for two consecutive years of the US CPS, DiMaggio and Bonikowski (2008) find evidence of a positive return to use the Internet only at work which is greater than the return to use the Internet only at home. Meanwhile, the returns to use both at home and at work are even greater. This indicates that skills and behaviors related to Internet use are rewarded in the labor market. According to the authors, workers may gain earning advantages by using the Internet at home through two mechanisms: social-capital/information-hoarding and cultural-capital/signaling about their qualifications.

3. Data

The data used in this study comes from a recent National Household Surveys for six Latin American countries: Brazil and Costa Rica for 2005, Chile for 2006, and Honduras, Mexico and Paraguay for 2007. All the surveys are representative at the national level and contain household and individual level information for many variables like income, economic activity, sector of activity, occupation, etc. With the exception of the Mexican dataset, which comes from an ad-hoc ICT survey, the surveys include a section of ICT related questions. Table IV.1 gives details on the data sources.

Table IV.1

National Household Surveys Description

Country	Year	Survey	Institution
Brazil	2005	Pesquisa Nacional por Amostra de Domicílios (PNAD)	Fundacao Instituto Brasileiro de Geografia e Estatistica (IBGE)
Chile	2006	Encuesta de Caracterización Socioeconómica Nacional (CASEN)	Ministerio de Planificación Nacional (MIDEPLAN)
Costa Rica	2005	Encuesta de Hogares de propósitos múltiples (EHPM)	Instituto Nacional de Estadística y Censos (INEC)
Honduras	2007	Encuesta Permanente de Hogares de Propósitos Múltiples (EPHPM)	Instituto Nacional de Estadística (INE)
Mexico	2007	Encuesta Nacional sobre Disponibilidad y Uso de las Tecnologías de la Información en los Hogares (ENDUTIH)	Instituto Nacional de Estadística y Geografía (INEGI)
Paraguay	2007	Encuesta Permanente de Hogares (EPH)	Dirección Nacional de Estadísticas, Encuestas y Censos (DNEEC)

Source: Author's elaboration.

As mentioned in the introduction, individual income is the outcome variable used to measure the impact of Internet use. Using income as the outcome variable incurs potentially serious endogeneity and selection problems. One first step to reduce them is to constrain the group of the population under analysis. Indeed, in order to avoid capturing the effect of variables related to gender and labor supply decisions and not ICT, the sample will be restricted when possible to full-time employed men.[4] Moreover, for the analysis of the impact of Internet use among salaried workers, the sample will be restricted even further to urban area workers. Table IV.2 shows information about sample sizes and prevalence of Internet use across the different surveys. The first column breaks down the individuals observations in two groups: Self-employed and Salaried workers. Column two reports the sample sizes of the corresponding groups in the different surveys. On average, self-employed workers represent nearly 30% of the workers in the sample, ranging from around 20% in Costa Rica to 40% in Honduras.

[4] Notwithstanding, for the case of Mexico the sample includes all male employed workers because there is no information on hours of work in the survey. In some exercises for the self-employed workers where the sample sizes were otherwise too small, women were included in the analysis. This is the case of Costa Rica, Mexico and Paraguay.

Table IV.2

Patterns of Internet use by full-time employed men in urban areas

(Number and percentages)

Country/Location	N	Internet use (%)					
		Anywhere	Work	Home	Only at work	Only at other places[a]	Work and other places
Brazil (2005)							
Self-employed	12 192	12.3%	6.7%	7.8%	1.6%	5.5%	5.2%
Salaried workers	31 212	25.9%	20.2%	12.4%	7.4%	5.8%	12.8%
Total	43 404	22.1%	16.4%	11.1%	5.8%	5.7%	10.6%
Chile (2006)							
Self-employed	5 947	12.6%	3.9%	7.0%	1.9%	8.8%	2.0%
Salaried workers	15 817	23.8%	14.6%	9.8%	9.7%	9.2%	5.0%
Total	21 764	20.8%	11.7%	9.0%	7.6%	9.1%	4.1%
Costa Rica (2005)							
Self-employed	436	13.5%	3.7%	6.0%	1.4%	9.9%	2.3%
Salaried workers	1 787	32.0%	22.2%	10.6%	10.7%	9.8%	11.5%
Total	2 223	28.4%	18.6%	9.7%	8.9%	9.8%	9.7%
Honduras (2007)							
Self-employed	2 116	12.7%	4.2%	5.0%	1.3%	8.4%	2.9%
Salaried workers	3 228	20.0%	12.5%	4.5%	6.5%	7.4%	6.0%
Total	5 344	17.1%	9.2%	4.7%	4.4%	7.8%	4.8%
Mexico (2007)[b]							
Self-employed	382	11.3%	2.6%	5.0%	1.8%	8.6%	0.8%
Salaried workers	1 424	31.4%	16.6%	10.8%	9.7%	14.4%	6.9%
Total	1 806	27.1%	13.6%	9.6%	8.0%	13.2%	5.6%
Paraguay (2007)							
Self-employed	389	5.9%	1.5%	2.1%	1.0%	4.4%	0.5%
Salaried workers	751	18.1%	10.9%	6.3%	8.5%	7.2%	2.4%
Total	1 140	13.9%	7.7%	4.8%	6.0%	6.2%	1.8%

Source: Author's elaboration based on National Household Surveys.

[a] *Includes access at home, education, public and commercial centers;*

[b] *Full-time and part-time workers were included in the sample, given that there is no information for hours of work.*

As mentioned before, the reason for separating these two employment categories for the analysis is based on the different patterns of Internet use they present. Indeed, columns three to eight report, respectively, the percentage of Internet users, users at work, at home, users only at work, only at other places and individuals who use the Internet both at work and at other places. Use at other places includes access to the Internet at home, educational centers, and communal and commercial common access points. It should be noted that the surveys allow respondents to report Internet use at more than one place simultaneously. Then it must be the case, as can be checked in Table IV.2, that the sum of the fractions of Internet users only at work and both at work and at other places should add up to the fraction of Internet users at work.

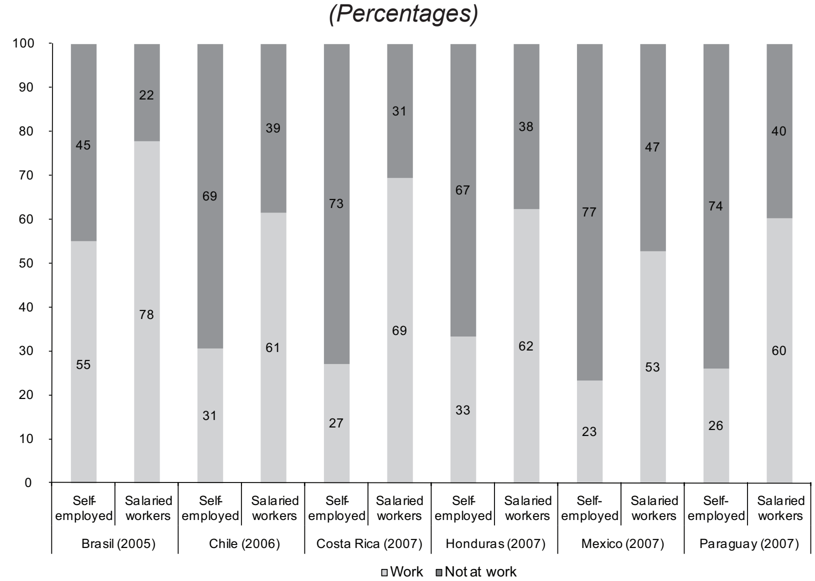
In all the surveys, Internet use prevalence is a lot greater for salaried workers than for the group of self-employed. Indeed, computing a simple average of the data in Table IV.2 across the six countries analyzed, only 12% of the self-employed use the Internet compared with more than 25% of users among wage employees. Internet use prevalence for self-employed workers is surprisingly similar in Brazil, Chile, Costa Rica, Honduras and Mexico and a little more spread for salaried workers. On the other hand, Paraguay presents the lowest fractions of Internet users among both types of workers in the sample. Indeed, only 6% and 18% of the self-employed and wage workers, respectively, reported use of the Internet at any place. The higher rate of Internet use among salaried workers is repeated when looking at use according to place of access.

Considering the different use types in relative terms, a clear pattern that emerges from the data is that while typically the salaried workers access the Internet at work, the self-employed access mainly at other places, and in particular at home. This can be observed in Figure IV.1 which shows the distribution of users by employment category according to place of access. On average, 64% and 32% of the Internet users among salaried and self-employed workers access at work, respectively. The remaining users for each employment category log on the web at other places including home. Figure IV.2 displays the percentage of Internet users at home among users in each employment category and country. Comparing the two employment groups across countries, the fraction of users at home is greater, in some cases by far, for the self-employed.

Figure IV.1

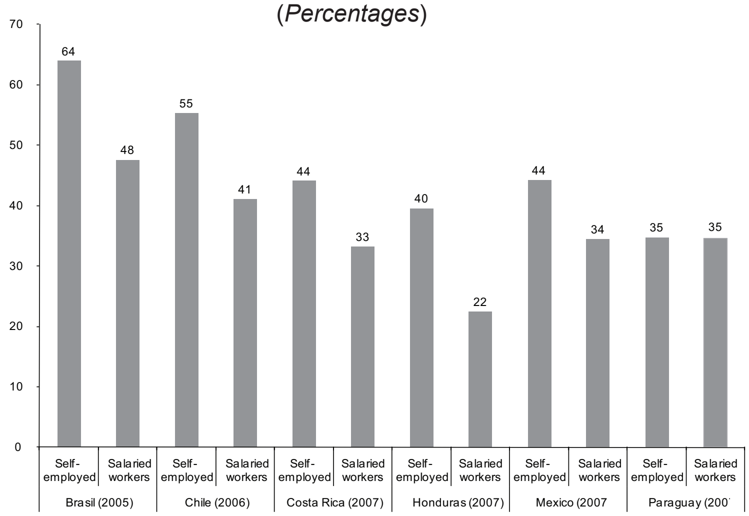
Distribution of Internet users by employment category and access point

(Percentages)



Source: Author's elaboration based on National Household Surveys.

Figure IV.2
Percentage of users at home by employment category
(*Percentages*)



Source: Author's elaboration based on National Household Surveys.

These patterns may also depict different interpretations of the impact of Internet use on income for the two employment categories that justify analyzing them separately. On the one hand, salaried workers do not pay directly for the Internet adoption decision at work. Therefore, the Internet premium could be associated to observables and unobservables for both firms and workers. On the other hand, for the self-employed, the adoption decision is completely endogenous and the return to Internet use is more likely to be related entirely to workers' characteristics.

Finally, it is relevant to focus on the impact of ICT on the self-employed given their disadvantaged status with respect to the salaried workers, particularly in Latin America. Indeed, the literature finds that most of the informal sector workers in the region are self-employed, earn less and have less education than their salaried counterparts (Maloney, 2004). In this context, it would be interesting to analyze to what extent the use of ICT can be a way to escape informality and its related problems. Given this, the present work evaluates the impact of Internet use on income of the salaried and self-employed workers separately. There are different research questions that emerge from the consideration of the two worker groups independently. In the case of wage workers, one question is whether use at home and work are substitutes or complements in terms of their impact on income. For the self-employed workers, given the importance of access at home another question is if there is a return to use of different Internet applications, *e.g.* whether there is a return to use for entertainment as opposed to a use for banking. A third question related to Internet use among independent workers is about the return to use for those who do not have access at home. This is relevant for public policies, in the sense of having a measure of the social impact of having free Internet access centers in communities.

4. Empirical Approach

Even if Internet use is associated to higher income, it is difficult to identify the direction of causality by simply observing the data. This reflects a selection problem that has to be dealt with when estimating the impact of Internet use on income. Ideally, one would like to know what the performance of individuals would have been if they did not use the Internet. Given that the Internet adoption decision is not random, it is not possible to observe the outcome for the individuals that do not use the Internet because that would incur a selection bias. Instead, a proper counterfactual of the outcome of users conditional on no use must be created. Different techniques can be used to deal with this issue. In our case, we implement the *Propensity Score Matching* (PSM) method (Rosenbaum and Rubin, 1983).

The treatment is then a dummy variable U_i (users) which takes a value of 1 if the individual uses the Internet and zero otherwise. The values of U_i determine the assignment of individuals to the treatment and control groups, correspondingly. Let Y^1_i be the outcome of individual i as a result of the treatment. The causal effect of Internet use on the outcome of the treated is then $Y^1_i - Y^0_i$ where Y^0_i is the outcome evaluated in case of no use ($U_i = 0$). Clearly, Y^0_i is not observable. It is standard to define the average effect of the treatment on the outcome variable as

$$E(Y^1_i - Y^0_i \mid U_i = 1) = E(Y^1_i \; U_i = 1) - E(Y^0_i \; U_i = 1).$$

While the first term is observed the second term is not. An estimator of this counterfactual widely used in the evaluation literature is,

$$E(Y^0_i \; U_i = 1) = E(Y^0_i \; P(X), U_i = 1) = E(Y^0_i \; P(X), U_i = 0),$$

where P(X) is the probability of Internet use conditional on a set of observable characteristics X. Note that the average value of the outcome should be independent of the treatment indicator (conditional independence). We also need to consider a range for P(X) such that the comparison of expected values between the control and treatment groups is feasible (common support).

Accordingly, we first estimate a Probit model for the probability of Internet use (propensity score) conditional on a set of observables X. We need then to find a control group very similar to the treatment group in terms of its predicted probability of Internet use (p_i). This requires choosing a set X of variables that are not influenced by the treatment (Todd, 1999), *i.e.* characteristics prior to the treatment. For our study, the elements of X should include variables that are thought to affect the probability of use but not the outcome. We include in the set of observables age, age squared, dummies for educational attainment (8 and 12 years), occupation, sector of activity, house type, house ownership, access to satellite TV, access to a landline telephone and access to a computer at home.[5] Many of these variables where included in order to control for the individuals' wealth, which is related to past income. Additionally, the Probit estimations for the probability of Internet use for salaried workers include a variable on establishment size to control for workplace characteristics. A description of the variables used in this procedure is presented in Table A.1 in the Appendix.

According to Todd (2008), there is no theoretical basis on how to choose X and which variables are included in X can have important implications for the estimator's performance. Rosenbaum and Robin (1983) propose as a specification (balancing) test to choose a set X such that there are no differences in X between the two groups after conditioning for P(X). In this study we follow the *psmatch2* procedure of *Stata* developed by Leuven and Sianesi (2003) which takes these problems into account. Once we have estimated the propensity scores, we match the groups using the method of the nearest neighbor. That is, for each user with propensity score p_i, an individual *j* is selected such that her propensity score p_j is as close as possible to p_j. After this procedure, we have then matched groups of users and non users. We can finally compute the effect of Internet use by comparing the outcomes of the two groups of matched observations. As commonly referred to in the evaluation literature, this is the Average Treatment on the Treated (ATT).

The procedure described above was run separately for the samples of salaried and self-employed workers in each survey. Before turning to the results, it is useful to evaluate the quality of the matching procedure. For this purpose, for each variable in X the average for the treated and control groups of the matched and unmatched samples and tested for differences in their respective means was computed. This information is partially summarized in Tables IV.3 and IV.4 for each of the estimates for salaried and self-employer workers, respectively. Indeed, these two tables report the standardized differences in the means of a sub-set of the variables included in the X vector. For each variable, the first row displays the mean differences between users and non-users before matching and their statistical significance. Additionally, the second row shows the same information computed with the sub-sample of matched observations.

Looking at the different variables in Tables IV.3 and IV.4 it is not surprising to note for instance that the percentage of users among the individuals with more years of education is greater (first two variables) in the unmatched sample. It is also observed that Internet usage is greater for younger people (variable Age). Also, those with a telephone and a computer at home are more likely to use the Internet. What the matching procedure does is precisely to select groups of treated and non-treated such that the difference between them in the probability of Internet is minimized. Then, the smaller differences between treated and controls in the matched samples for all the variables are an indication of a

[5] The information for house type and ownership is not available for Mexico.

good matching quality. Moreover, for most of the variables those differences become not statistically different from zero.[6]

Table IV.3

Percentage difference in means between treated and controls before and after matching selected variables for salaried workers

Variable	Sample	Brazil		Chile		Costa Rica		Honduras		Mexico		Paraguay	
8 or more years of education [a]	Unmatched	157.0	***	110.9	***	147.3	***	135.8	***	103.6	***	120.9	***
	Matched	-2.1		-0.1		0.6		1.8		-2.6		-2.6	
12 or more years of education [a]	Unmatched	103.7	***	119.5	***	140.9	***	93.1	***	134.8	***	101.0	***
	Matched	1.7		1.9		6.1		4.7		-4.3		-5.4	
Age	Unmatched	-5.4	***	-36.7	***	-3.9		-10.3	*	-11.0		-14.2	
	Matched	-3.5		-1.9		3.2	**	0.8		-7.2	**	-1.2	
Landline telephone at home [a, b]	Unmatched	79.2	***	65.9	***	39.6	***	65.7	***	59.2	***	68.6	***
	Matched	-0.7		-2.5		16.1	**	-1.0		-5.2		-5.3	
Satellite TV at home [a, b]	Unmatched	24.6	***	70.2	***	68.5	***	69.4	***	74.9	***	86.0	***
	Matched	0.1		2.6		5.0		-0.2		3.2		2.2	
PC at home [a, b]	Unmatched	129.8	***	109.2	***	109.4	***	93.5	***	108.9	***	107.1	***
	Matched	-2.1		0.3		-6.3		-2.3		-4.6		-8.1	
Live in house [a, b]	Unmatched	-62.8	***	-24.4	***	-13.7	***	19.4	***	n.a.	n.a.	-16.2	*
	Matched	-2.3		1.4		-12.6	**	0.9		n.a.	n.a.	-5.4	
Live in apart-ment [a, b]	Unmatched	65.8	***	30.0	***	24.9	***	15.5	***	n.a.	n.a.	33.1	***
	Matched	2.3		-1.0		10.0	*	3.2		n.a.	n.a.	11.1	
Property Owner [a, b]	Unmatched	-11.2	***	-47.8	***	-7.0	***	3.7		n.a.	n.a.	-19.3	**
	Matched	-0.8		1.4		5.8		2.4		n.a.	n.a.	-5.0	
Tenant [a, b]	Unmatched	8.1	***	24.3	***	8.4	*	-9.3	**	n.a.	n.a.	25.7	***
	Matched	-0.6		1.8		-13.3	**	-0.2		n.a.	n.a.	15.6	
Owner Paying Mortgage [a, b]	Unmatched	20.7	***	35.3	***	14.7	***	22.4	***	n.a.	n.a.	-2.9	
	Matched	-0.3		-2.4		6.5		-2.8		n.a.	n.a.	1.8	

Source: Author's elaboration based on National Household Surveys.

[a] *Fraction of individuals in the sample.*

[b] *Obtained from the corresponding categorical variables used for the matching procedure.*

, ** and * indicate statistical significance at 10%, 5% and 1% levels, respectively. Detailed information for all the variables included in the propensity score estimation is presented in the Appendix.*

[6] The only exception is the case of Costa Rica for the sample of salaried workers (see Table IV.3). Even though the procedure reduces the mean differences between treated and controls, they remain significant for some variables.

Table IV.4
Percentage difference between treated and controls before and after matching selected variables for self-employed workers

Variable	Sample	Brazil		Chile		Costa Rica		Honduras		Mexico		Paraguay	
8 or more years of education [a]	Unmatched	207.1	***	161.8	***	158.9	***	115.5	***	146.8	***	155.5	***
	Matched	-2.1		0.5		20.4		3.1		4.0		-0.2	
12 or more years of education [a]	Unmatched	111.7	***	115.8	***	119.5	***	65.1	***	124.5	***	114.9	***
	Matched	7.8		-0.9		-7.8		6.3		2.8		-1.2	
Age	Unmatched	-24.5	***	-57.2	***	-23.3	*	-24.2	***	-40.5	***	-38.5	***
	Matched	-5.6	**	-4.5		-0.5		9.5		4.0		-0.3	
Landline telephone at home [a, b]	Unmatched	126.1	***	112.4	***	33.5	***	105.8	***	61.0	***	79.4	***
	Matched	2.2		2.8		-21.3		-0.2		1.7		0.4	
Satellite TV at home [a, b]	Unmatched	51.4	***	103.0	***	84.4	***	100.1	***	56.3	***	86.9	***
	Matched	-0.7		-5.5		4.5		3.8		15.5		-5.7	
PC at home [a, b]	Unmatched	178.0	***	170.6	***	118.6	***	136.2	***	97.7	***	118.4	***
	Matched	-5.3		-0.1		-7.7		-0.2		13.0		-3.5	
Live in house [a, b]	Unmatched	-73.0	***	-18.8	***	-42.9	***	-3.2	***	n.a.		-25.0	***
	Matched	-3.0		-7.8	*	-12.1		3.8		n.a.		-2.4	
Live in apartment [a, b]	Unmatched	75.2	***	36.0	***	36.3	***	19.1	***	n.a.		34.9	***
	Matched	3.2		8.5		1.3		-2.8		n.a.		1.2	
Property owner [a, b]	Unmatched	-36.1	***	-61.7	***	-46.7	***	-39.2	***	n.a.		-28.8	***
	Matched	2.9		-6.8		-6.8		-0.2		n.a.		0.0	
Tenant [a, b]	Unmatched	36.7	***	45.0	***	34.0	***	36.2	***	n.a.		44.0	***
	Matched	-9.2	**	4.0		28.1		6.0		n.a.		3.2	
Owner paying mortgage [a, b]	Unmatched	22.8	***	41.2	***	24.9	***	20.4	***	n.a.		4.2	***
	Matched	3.7		4.9		-25.6		-2.1		n.a.		-3.9	

Source: Author's elaboration based on National Household Surveys.
[a] *Fraction of individuals in the sample.*
[b] *Obtained from the corresponding categorical variables used for the matching procedure.*
, ** and * indicate statistical significance at 10%, 5% and 1% levels, respectively. Detailed information for all the variables included in the propensity score estimation is presented in the Appendix.*

5. Estimation results

(a) Salaried workers

Table IV.5 summarizes the results for the ATT of Internet use on income for salaried workers and different control groups. There were performed five different experiments using this sample of workers.[7] The first row reports the return to Internet use, where the

[7] The details for the number of treated and controls before and after matching are in Tables A.2 – A.7 in the Appendix.

treatment and control groups include users anywhere and non users, respectively. These results indicate a positive and statistical significant impact of Internet use on earnings for all countries but Paraguay.[8] The earning advantage of salaried users ranges between near 18% in Mexico and around 30% in Brazil and Honduras.

These returns are above the obtained in the literature for developed countries with similar datasets. As mentioned before, Goss and Phillips (2002), Freeman (2002) and Mossberger *et al.* (2006) obtained returns to Internet use of around 15% using similar cross-sectional data for the US. Only the estimated returns for Chile and Costa Rica are near the US estimates. One reason for the higher returns in Latin America may be the lower dissemination of Internet use compared with the developed countries figures. With diminishing returns to use, returns would be expected to decrease over time as prevalence increases. Another factor to consider is that the unmatched differences between treated and non-treated are too large to start with as to also expect large returns based on the matched samples. Indeed, the average differences in income between users and non-users in the matched sample represents between 20 and 35% of the corresponding differences in the unmatched samples (for details see Tables A.2 – A.7 in the Appendix).

Table IV.5

ATT of Internet use for full-time salaried men in urban areas

Groups		**ATT**					
Treated	**Control**	**Brazil**	**Chile**	**Costa Rica**	**Honduras**	**Mexico**[a]	**Paraguay**
Use	Not use	0.297***	0,260***	0.243***	0.302***	0.176***	0.145
Use only at work	Not use	0.253***	0.284***	0.275***	0.371***	0.289***	0.212**
Use only at other places	Not use	0.170***	0.168***	0.039	0.189***	0.122*	0.179
Use at work and other places	Not use	0.420***	0.417***	0.325***	0.356***	0.318***	0.521**
Use at work and other places	Use only at work	0.196***	0.129***	0.034	0.142	0.088	0.458*

Source: Author's elaboration based on estimation results.
[a] Full time and part time workers were included in the sample.
, ** and * indicate statistical significance at 10%, 5% and 1% levels, respectively.*

Rows two to four of Table IV.5 present the results of the ATT of different types of Internet use according to place of access. Indeed, the treatment was decomposed for those who only use the Internet at work (results of row two), those who only use it at other places (row three) and those who access the web both at work and at other places (row four). In a way, the results for the last case may indicate whether uses at work and other places are substitutes or complement. In the three cases considered only the non-users are included in the control group.

[8] Indeed, the return to use for salaried workers in Paraguay is around 14%, but the statistical significance is slightly above the 10% level (see Table A.7 in the Appendix).

The results show that for all countries there is a positive and statistical significant effect of use only at work which is always greater than the return to use only at other places. Furthermore, while the return to use only at work is positive for all countries, the return to use only at other places (mainly at home) is not statistically different from zero in Costa Rica and Paraguay. Notwithstanding, when the use at other places is combined with use at work, the returns on earnings are positive and much higher than the returns to use exclusively at one place for all the countries. In line with what DiMaggio and Bonikowski (2008) find for the US, these results suggest that Internet use both at home and at work are complements in Latin America.

A final exercise evaluates the ATT of Internet use at work and other places simultaneously conditional on using Internet at work. In a way this experiment would control for the potential problem of the previous experiments that use might be correlated with unobserved abilities. This problem is probably mitigated by restricting the sample to those who use the Internet and therefore may have already acquired the skills to do so. Results, reported in the last row of Table IV.5, reveal much smaller returns. Indeed, they turned out statistically different from zero only in Brazil, Chile and Paraguay.

(b) Self-employed workers

Table IV.6 presents different exercises of the ATT of Internet use for the sample of self-employed workers. As mentioned before, given otherwise too small sample sizes, the dataset for Costa Rica, Mexico and Paraguay includes both men and women. Like in Table IV.5, the first row reports the returns to use versus non-use on earnings. As can be noted, the ATT are positive and statistically significant for all the countries but Costa Rica, where it is positive but the small sample size probably affects the standard errors of the estimates. Comparing these results with those of the first row of Table IV.5, we observed similar returns to Internet use for the wage workers and the self-employed in Brazil and Honduras, relatively greater returns for the wage workers in Chile and Costa Rica, and exactly the opposite in Mexico and Paraguay.

The following rows of Table IV.6 display the ATT for four other exercises. Row two shows the ATT of use with no access at home in which case the control group is composed of those with no access who do not use the Internet. Since most of the self-employed do not use the Internet at work and the treatment exclude those with access at home, the results in this case would capture the return to use at common places for those with no access. Notwithstanding, the problem with this exercise is that the ATTs might be contaminated by the ability bias toward users among individuals with no access. Anyway, results indicate a significant positive return in four of the six countries analyzed. Indeed, the returns to use for those with no access at home are particularly high for Brazil (33%), intermediate for Honduras and Paraguay (around 20%) and relatively lower for Chile (14%).

Table IV.6
ATT of Internet use for full-time self-employed men

Groups		ATT					
Treated	*Control*	*Brazil*	*Chile*	*Costa Rica*[c]	*Honduras*	*Mexico*[c, d]	*Paragua* [c]
Use	Not use	0.271***	0,182***	0.202	0.314***	0.318**	0.236***
Use with no access at home	Not use and no access	0.328***	0.138**	0.162	0.217**	0.252	0.201***
Use at home	Use somewhere else	-0.018	0.133	0.199	0.313	n.a.	0.14
Use at home[a]	Use somewhere else	0.073	0.134	0.813	0.787**	n.a.	0.307
Use for productive purposes[b]	Other use	0.258***	0.188**	0.381	-0.305	0.097	-0.057

Source: Author's elaboration based on estimation results.
[a] ATT on other household members income.
[b] Includes use for communication, banking and government.
[c] Men and women were included to avoid sample size problems.
[d] Full time and part time workers were included in the sample.
, ** and * indicate statistical significance at 10%, 5% and 1% levels, respectively.*

Rows three and four of Table IV.6 approximate the returns to use at home among Internet users. As mentioned above, restricting the sample to users would eventually reduce the effect of unobserved variables related to workers' abilities. There are two impact variables considered in this experiment. First, the individual income, and second the income of the other household members. Results in this case are unfortunately not very promising and the reason is probably that the sample sizes are too small probably leading to large standard errors. Furthermore, it was not possible to perform the experiment for Mexico because all the users in the sample use the Internet at home. Anyway, for all the cases the returns on other household members are greater than the ones for the self-employed individuals.

A final exercise of interest for the self employed is to explore whether there is a differential return to the use of different Internet applications. It would be hard to believe that using the Internet for entertainment would have an impact on income. For this reason, the individual who use the web in activities that would have productive purposes —communication, banking and e-government— were grouped in particular category. The last row of Table III.6 displays the ATT of Internet use for productive purposes on individual earnings considering in the control group other Internet users. When data availability made it possible, the treated are those who use the Internet for communication, banking and interaction with the government.[9] Even when for most of the cases the results are not satisfactory because of the small sample sizes, it is observed a positive and statistically significant return to productive use of the Internet on earnings in Brazil and Chile.

[9] For Costa Rica, there is no information on Internet use for government. For Paraguay and Honduras only use for communication was included.

6. Concluding remarks

This paper constitutes one of the first attempts to measure the impact of Internet use on earnings in Latin America. The analysis utilizes cross-sectional data coming from recent household surveys for Brazil, Chile, Costa Rica, Honduras, Mexico and Paraguay. The empirical results reflect a sizable return to Internet use for both salaried and self-employed workers which range between 18 and 30%. These figures are much higher than those obtained for the US using similar data. As mentioned throughout the paper, the lack of information on individual pre-treatment characteristics may bias upwards the estimated returns. For this reason, the results of this study might be taken as an upper bound for the returns to Internet use. The results are large enough as to suggest that there is a positive impact of web use on earnings in Latin America.

Other relevant results are the following. First, Internet usage at home and usage at work by salaried workers are complements with respect to their impact on earnings. Second, there is a positive return to use on earnings for those self-employed workers who have no access at home and at work. Third, there is some evidence of a positive return to use for productive purposes with respect to use for other reasons among the self-employed. Finally, there is some evidence of a positive return to access at home conditional on use for salaried workers but not for the self-employed.

The findings of this research would be enriched if longitudinal data on ICT usage in the region would be available. Also, in order to have a more accurate measure of the impacts of the new ICT more specific data are needed. This includes, for instance, having information on ICT usage experience, intensity, and other characteristics. Also, the availability of matched employer-employee data in the region would be also useful to better understand the interaction between firms and workers in terms of ICT investments and returns. In some cases this data is partially available but it would be desirable to have a systematic collection of new ICT data in the region.

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8. Appendix

Table A.1
Description of variables included in propensity score estimations

Variables	Description
8+ years of education	1: Yes; 0: No.
12+ years of education	1: Yes; 0: No.
Age	Years of Age
Age squared	Years of Age Squared
Urban Areas	1: Yes; 0: No.
Sex	1: Male; 2: Female.
Sector of Activity (*aggregation of categories may differ across countries*)	1, Agriculture, hunting and forestry; 2, Fishing; 3, Mining and quarrying; 4, Manufacturing; 5, Electricity, gas and water supply; 6, Construction; 7, Wholesale and retail trade; repair of motor vehicles/ motorcycles and personal and household goods; 8, Hotels and restaurants; 9, Transport, storage and communications; 10, Financial intermediation; 11, Real estate, renting and business activities; 12, Public administration and defense; compulsory social security; 13, Education; 14, Health and social work; 15, Other community, social and personal service activities; 16, Activities of private households as employers and undifferentiated production activities of private households; 17, Extraterritorial organizations and bodies;18 Other activities, 99, Unknown; 19, Agriculture, hunting, forestry and fishing; 20, Manufacturing, electricity, gas and water supply; 21, Education, health and social services; 22, Wholesale and retail trade; repair of motor vehicles, motorcycles, hotels and restaurants; 23, Financial int.
Occupation	1, Legislators, senior officials and managers; 2, Professionals; 3, Technicians and associate professionals; 4, Clerks; 5, Service workers and shop and market sales workers; 6, Skilled agricultural and fishery workers; 7, Craft and related trades workers; 8, Plant and machine operators and assemblers; 9, Not qualified workers; 10, Armed Forces; 11, Other activities; 99 Unknown.
Size of Establishment	Different categorical variables for each country.
House Type	1, House; 2, Apartment; 3, Room in a house or shared house; 4, Improvised house; 8, Other; 9, Unknown.
House Ownership	1, Owned- paid; 2, Owned- paying; 3, Rented; 4, Family owned; 5, Owned; 8, Other; 9, Unknown.
Landline Phone at Home	1: Yes, 2: No, 9: Unknown.
Satellite TV at Home	1: Yes, 2: No, 9: Unknown.
Computer at Home	1: Yes, 2: No, 9: Unknown.

Source: Author's own elaboration.

Table A.2

ATT salaried workers – Brazil

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	7 288	23 056			
Unmatched	7.393	6.342	1.051	0.009	118.24
ATT	7.320	7.023	0.297	0.022	13.34
		b. Users only at work versus non-users			
N	22 658	2 079			
Unmatched	7.114	6.348	0.766	0.014	55.46
ATT	7.039	6.786	0.253	0.020	12.54
		c. Users at other places versus non-users			
N	23 035	1 616			
Unmatched	7.033	6.342	0.691	0.015	44.67
ATT	6.978	6.807	0.170	0.025	6.82
		d. Users both at work and other places versus non-users			
N	22 692	3 585			
Unmatched	7.718	6.348	1.371	0.011	121.43
ATT	7.683	7.264	0.420	0.039	10.8
		e. Users both at work and other places versus other users at work			
N	2 309	3 580			
Unmatched	7.718	7.114	0.604	0.021	28.92
ATT	7.684	7.488	0.196	0.033	5.88

ATT self-employed workers – Brazil

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	1 374	15 784			
Unmatched	7.472	6.148	1.324	0.023	56.63
ATT	7.427	7.156	0.271	0.057	4.75
		b. Users with no access versus others with no access			
N	461	15 138			
Unmatched	7.089	6.111	0.978	0.037	26.19
ATT	7.045	6.717	0.328	0.049	6.68
		c. Users at home versus users somewhere else			
N	792	128			
Unmatched	7.683	7.487	0.197	0.079	2.48
ATT	7.717	7.735	-0.018	0.092	-0.2
Unmatched*	7.311	7.067	0.244	0.114	2.13
ATT*	7.349	7.276	0.073	0.148	0.49
		d. Users for productive purposes versus other users			
N	1 104	298			
Unmatched	7.594	6.990	0.603	0.055	11.04
ATT	7.526	7.268	0.258	0.077	3.33

Source: Author’s own elaboration.
*Note: The outcome variable is individual income in logs. * The outcome variable is income for other household members.*

Table A.3
ATT salaried workers - Chile

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	3 366	11 961			
Unmatched	13.124	12.270	0.854	0.012	70.84
ATT	13.047	12.787	0.260	0.023	11.18
		b. Users only at work versus non-users			
N	1 376	11 958			
Unmatched	13.049	12.270	0.779	0.016	47.47
ATT	13.006	12.722	0.284	0.026	10.81
		c. Users at other places versus non-users			
N	1 294	11 958			
Unmatched	12.963	12.270	0.693	0.017	40.76
ATT	12.885	12.717	0.168	0.027	6.25
		d. Users both at work and other places versus non-users			
N	625	11 626			
Unmatched	13.571	12.276	1.295	0.022	58.08
ATT	13.493	13.077	0.417	0.048	8.64
		e. Users both at work and other places versus other users at work			
N	695	1 518			
Unmatched	13.568	13.052	0.516	0.034	15.35
ATT	13.519	13.390	0.129	0.049	2.64

ATT self-employed workers - Chile

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	787	11 058			
Unmatched	13.491	12.485	1.006	0.031	32.14
ATT	13.432	13.250	0.182	0.054	3.4
		b. Users with no access versus others with no access			
N	330	10 628			
Unmatched	13.162	12.458	0.704	0.046	15.25
ATT	13.088	12.950	0.138	0.058	2.4
		c. Users at home versus users somewhere else			
N	390	360			
Unmatched	13.729	13.210	0.520	0.066	7.9
ATT	13.732	13.599	0.133	0.114	1.17
Unmatched*	12.504	11.805	0.699	0.142	4.93
ATT*	12.554	12.419	0.134	0.203	0.66
		d. Users for productive purposes versus other users			
N	509	304			
Unmatched	13.610	13.261	0.350	0.067	5.19
ATT	13.541	13.353	0.188	0.077	2.43

Source: Author's own elaboration.
*Note: The outcome variable is individual income in logs. * The outcome variable is income for other household members.*

Table A.4

ATT salaried workers – Costa Rica

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	515	1 173			
Unmatched	12.971	12.237	0.735	0.029	25.36
ATT	12.950	12.707	0.243	0.059	4.09
		b. Users only at work versus non-users			
N	171	914			
Unmatched	13.032	12.293	0.738	0.042	17.66
ATT	13.011	12.736	0.275	0.079	3.48
		c. Users at other places versus non-users			
N	156	1 153			
Unmatched	12.634	12.237	0.397	0.042	9.35
ATT	12.587	12.549	0.039	0.069	0.56
		d. Users both at work and other places versus non-users			
N	166	856			
Unmatched	13.205	12.315	0.889	0.041	21.59
ATT	13.188	12.863	0.325	0.095	3.42
		e. Users both at work and other places versus other users at work			
N	182	186			
Unmatched	13.205	13.040	0.166	0.064	2.57
ATT	13.199	13.166	0.034	0.083	0.4

ATT self-employed workers – Costa Rica

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	73	893			
Unmatched	12.650	11.696	0.953	0.080	11.94
ATT	12.487	12.285	0.202	0.127	1.6
		b. Users with no access versus others with no access			
N	38	847			
Unmatched	12.372	11.677	0.695	0.099	7.04
ATT	12.192	12.030	0.162	0.117	1.38
		c. Users at home versus users somewhere else			
N	18	48			
Unmatched	12.830	12.402	0.428	0.133	3.22
ATT	12.810	12.610	0.199	0.234	0.85
Unmatched*	11.890	10.765	1.126	0.395	2.85
ATT*	11.847	11.034	0.813	0.676	1.2
		d. Users for productive purposes versus other users			
N	18	53			
Unmatched	12.844	12.197	0.647	0.196	3.29
ATT	12.844	12.462	0.381	0.239	1.6

Source: Author's own elaboration.
*Note: The outcome variable is individual income in logs. * The outcome variable is income for other household members.*

Table A.5

ATT salaried workers – Honduras

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	549	2 553			
Unmatched	9.336	8.472	0.864	0.030	28.94
ATT	9.299	8.997	0.302	0.049	6.17
		b. Users only at work versus non-users			
N	180	2 274			
Unmatched	9.452	8.521	0.931	0.045	20.78
ATT	9.441	9.070	0.371	0.071	5.26
		c. Users at other places versus non-users			
N	212	2 340			
Unmatched	9.015	8.515	0.500	0.042	11.84
ATT	8.977	8.789	0.189	0.059	3.19
		d. Users both at work and other places versus non-users			
N	151	2 335			
Unmatched	9.646	8.515	1.131	0.049	23.09
ATT	9.602	9.247	0.356	0.088	4.04
		e. Users both at work and other places versus other users at work			
N	151	198			
Unmatched	9.658	9.456	0.202	0.080	2.54
ATT	9.676	9.534	0.142	0.096	1.49

ATT self-employed workers - Honduras

	Treated	Controls	Difference	SE	t-stat
		a. Users versus non-users			
N	240	3 473			
Unmatched	9.491	8.041	1.450	0.079	18.25
ATT	9.445	9.131	0.314	0.094	3.35
		b. Users with no access versus others with no access			
N	155	3 436			
Unmatched	9.190	8.026	1.164	0.097	11.98
ATT	9.147	8.930	0.217	0.092	2.36
		c. Users at home versus users somewhere else			
N	63	107			
Unmatched	10.004	9.366	0.638	0.140	4.55
ATT	9.956	9.643	0.313	0.207	1.51
Unmatched*	9.437	8.166	1.271	0.235	5.4
ATT*	9.386	8.599	0.787	0.383	2.06
		d. Users for productive purposes versus other users			
N	139	11			
Unmatched	9.670	9.475	0.195	0.314	0.62
ATT	9.684	9.989	-0.305	0.290	-1.05

Source: Author’s own elaboration.
*Note: The outcome variable is individual income in logs. * The outcome variable is income for other household members.*

Table A.6

ATT salaried workers – Mexico

	Treated	Controls	Difference	SE	t-stat
a. Users versus non-users					
N	376	921			
Unmatched	8.954	8.419	0.535	0.033	16.38
ATT	8.893	8.717	0.176	0.057	3.09
b. Users only at work versus non-users					
N	115	721			
Unmatched	9.005	8.447	0.558	0.048	11.63
ATT	8.980	8.691	0.289	0.079	3.67
c. Users at other places versus non-users					
N	174	921			
Unmatched	8.787	8.419	0.368	0.041	9.05
ATT	8.749	8.627	0.122	0.068	1.79
d. Users both at work and other places versus non-users					
N	78	437			
Unmatched	9.264	8.497	0.767	0.062	12.33
ATT	9.167	8.848	0.318	0.103	3.08
e. Users both at work and other places versus other users at work					
N	81	124			
Unmatched	9.262	9.014	0.248	0.094	2.64
ATT	9.241	9.154	0.088	0.117	0.75

ATT self-employed workers – Mexico

	Treated	Controls	Difference	SE	t-stat
a. Users versus non-users					
N	53	765			
Unmatched	8.768	7.917	0.851	0.123	6.94
ATT	8.533	8.215	0.318	0.137	2.32
b. Users with no access versus others with no access					
N	36	721			
Unmatched	8.566	7.895	0.671	0.153	4.38
ATT	8.418	8.167	0.252	0.162	1.56
c. Users at home versus users somewhere else					
N	na	na			
Unmatched	10.208	10.113	0.095	0.964	0.1
ATT	.	.	.	.	.
Unmatched*	9.065	9.234	-0.169	0.634	-0.27
ATT*	.	.	.	.	.
d. Users for productive purposes versus other users					
N	34	23			
Unmatched	8.842	8.605	0.237	0.244	0.97
ATT	8.842	8.745	0.097	0.250	0.39

Source: Author's own elaboration.
Note: The outcome variable is individual income in logs. * The outcome variable is income for other household members.*

Table A.7
ATT salaried workers – Paraguay

	Treated	Controls	Difference	SE	t-stat
a. Users versus non-users					
N	123	579			
Unmatched	14.870	14.145	0.725	0.056	12.87
ATT	14.812	14.667	0.145	0.091	1.58
b. Users only at work versus non-users					
N	58	500			
Unmatched	14.829	14.211	0.617	0.073	8.5
ATT	14.783	14.571	0.212	0.104	2.02
c. Users at other places versus non-users					
N	47	571			
Unmatched	14.798	14.148	0.650	0.084	7.78
ATT	14.749	14.570	0.179	0.123	1.46
d. Users both at work and other places versus non-users					
N	13	222			
Unmatched	15.233	14.353	0.880	0.148	5.93
ATT	15.099	14.579	0.521	0.242	2.15
e. Users both at work and other places versus other users at work					
N	11	46			
Unmatched	15.232	14.837	0.395	0.168	2.35
ATT	15.262	14.804	0.458	0.237	1.94

ATT self-employed workers - Paraguay

	Treated	Controls	Difference	SE	t-stat
a. Users versus non-users					
N	240	2 182			
Unmatched	14.923	13.976	0.948	0.057	16.52
ATT	14.886	14.650	0.236	0.079	3
b. Users with no access versus others with no access					
N	164	2,162			
Unmatched	14.738	13.969	0.769	0.068	11.38
ATT	14.695	14.495	0.201	0.078	2.58
c. Users at home versus users somewhere else					
N	62	93			
Unmatched	15.206	14.815	0.392	0.122	3.21
ATT	15.170	15.030	0.140	0.164	0.86
Unmatched*	14.780	14.280	0.499	0.153	3.26
ATT*	14.763	14.456	0.307	0.209	1.47
d. Users for productive purposes versus other users					
N	167	72			
Unmatched	14.924	14.921	0.003	0.114	0.02
ATT	14.909	14.966	-0.057	0.123	-0.46

Source: Author's own elaboration.
Note: The outcome variable is individual income in logs. The outcome variable is income for other household members.*

IV. Gender differences in Internet use

Lucas Navarro[1]
Martha Sánchez

1. Introduction

There is no doubt about the profound socio-economic impact of the diffusion of the Internet in modern societies. Indeed, the benefits are related to higher levels of productivity at work, higher efficiency of use of time, lower information costs and better learning techniques for students, among others. As it is the case with any new technology, the diffusion of the Internet is not homogeneous in a society. Indeed, at the initial stages of diffusion, access and usage is restricted to those who have the appropriate skills and can afford the cost of the new technology. This creates a pattern of Internet use and adoption that replicates the patterns of inequalities among other important socio-economic variables. In general, the literature has labeled this heterogeneous pattern of adoption of information and communication technologies (ICT) with the term *digital divide* and more recently *digital inequality*. One major concern for policy makers is that if there are benefits to Internet adoption, high inequality in ICT adoption can be a new source of pre-existent socio-economic inequalities (Di Maggio *et al*., 2004).

Motivated on the above, many studies have examined how socio-economic characteristics across different population groups affect the digital divide. The investigation of these factors has been a subject of analysis by a growing literature for Latin American countries, a region with high levels of inequality in Internet usage and access (Peres and Hilbert, 2009; Grazzi and Vergara, 2010, Grazzi, 2010) Given the widespread and persistent gender differentials in the labor market, partly explained by discrimination against women,[2] there is also an increasing interest in investigating the role of gender in the digital divide.

This paper contributes to an almost inexistent literature on the topic for Latin America.[3] It analyzes the gender role of the digital divide in Internet usage based on National Household Surveys for six Latin American countries: Brazil, Chile, Costa Rica, Honduras, Mexico and Paraguay. The article first presents a profile of gender inequalities in Internet use by groups of individuals classified according to geographic area of residence, age,

1 The authors thank Cesar Cristancho for statistical assistance and Matteo Grazzi, Marcela Perticará, Javiera Selman, Miguel Torres, Sebastián Vergara and Manuel Willington for very helpful conversations. Usual disclaimers apply.
2 Some studies for Latin America are Morrison *et al.* (2007) and Abramo and Valenzuela (2005).
3 Only Sánchez (2010) for Chile and Mexico and Hilbert (2010) have studied the digital gender divide in the region.

education, income quintiles, labor market status, point of access to the Internet and type of Internet application. Second, it estimates a model for the determinants of the probability of Internet use based on different individuals' characteristics.

Results suggest that on average there is a gender Internet use divide against women in the region. It is observed that the gender digital divide is more frequent in urban rather than in rural areas; that it affects older women of all education levels and that it tends to be more prevalent in the middle and upper ends of the household income distribution. There is also no evidence of gender digital inequalities in Internet use at work. Latin American women are also more likely to use the Internet at common access points than men. Moreover, women are more likely to use it for education and communication purposes than men, who are more likely to use the web for entertainment and e-commerce. The econometric analysis indicates that controlling for different characteristics including geographical area of residence, age, education, income, labor market status and other workers' characteristics, gender does not significantly affect the probability of Internet use at any place and at home. There are, however, some unexplained gender differences in Internet use indicating an up to 4% and 6% lower probability of women to use the Internet at any point of access and at home, respectively. Also, unexplained gender gaps in Internet use at work and by students are practically inexistent. These results combined with what it is observed in the data suggest that the gender digital divide exists but it is mainly a result of different men and women characteristics.

The paper is structured as follows. Next section discusses the literature on gender digital divide. Then, Section 3 presents the data and the main patterns of Internet use by gender in the appraised countries. Section 4 describes the empirical approach and section 5 discusses the econometric results. Finally, Section 6 concludes.

2. Literature

Along with the rapid diffusion of ICT in the last decades, the amount of literature analyzing the role of gender in Internet usage and adoption has increased rapidly. Some studies focus on whether there is a gender digital divide and others analyze the reasons for the difference in use among different population groups, including the gender dimension. Evidence regarding whether there is a gender digital divide or not is mixed. The first studies on the subject like Shashaani (1997) find evidence of greater computer use rates by males than females among university students in the US. Venkatesh *et al.* (2000) reported similar results and also observed a reduction in gender gaps in computer use based on census data for the period 1984-1997. Using data for three different years during the nineties in the US, Bimber (2000) find evidence of statistically significant gender gaps in Internet access and use. While both gaps are the product of socio-economic factors, the access gap is a result of some combination of underlying gender-specific phenomena. The reasons discussed are the existence of gender stereotyping, Internet contents that favor men, gender differences in communication styles, among others. When considering the analysis at household level, gender gaps in use might be reduced by the fact that Internet adoption is a collective decision as claimed by Carveth and Kretchmer (2002).

Ono and Zavodni (2005) analyze gender differentials in the rates of Internet use in households with Internet access in Japan and the US using micro-data for several surveys in the period 1997-2001. Controlling for socio-economic characteristics, the authors observe higher Internet use rates among men than women in both countries in 1997 and a reduction of the gender gap in 2001 in the US but not in Japan. Chen and Wellman (2004) find a diverging trend in gender digital inequalities in a study using micro-data for eight countries (US, UK, Germany, Italy, Japan, South Korea, China and Mexico). However, more recent research shows a different path. Indeed, a study about ICT usage in OECD countries (OECD, 2007) finds that the gender gap in Internet use has almost disappeared.[4] Evidence for China reported by CNNIC (2010) shows a significant increase in Internet penetration between 2003 and 2009 together with a reduction in gender disparities.[5] To summarize, the most recent international evidence indicate that the gender digital divide still exists but it is declining over time.

Perhaps given the tendency towards a reduction of the gender digital divide in access and use in many countries, another strand of papers have analyzed the digital gender gap in aspects like types and frequency of use and attitudes towards Internet usage among both adults and students. Some examples of these studies are Kennedy *et al.* (2003), Hargitai and Shafer (2006) and Hargittai and Hinnant (2008) for the US, Liff and Shepherd (2004) for the UK, Codoban (2005) for Romania and Brown and Czerniewicz (2009) for South Africa. These articles detect gender gaps in skills and attitudes towards Internet use that explain lower usage rates by females. They also identify gender differences in revealed preferences for different types of use. Indeed, results indicate that women typically use the Internet for social reasons and males use it for information, commerce and entertainment.

From a different perspective, Chen (2004) uses data for a panel of countries to investigate the effects of the level of ICT infrastructure on gender inequality and employment. The results indicate that the level of ICT infrastructure exerts a statistically significant positive effect on gender equality in education. This suggests that improvements in the level of ICT infrastructure lead to improvements in gender equality in education and labor force participation. One possible reason suggested by the author for this positive effect is that the availability of ICT allows women to work from home.

4 Similar conclusions are suggested by Jackson (2008) for the US and Dwivedi and Lal (2007) in a study about broad-band adoption in the UK.

5 By 2009, Internet penetration rates for males and females were 73% and 67%, respectively.

Concerning the evidence for Latin America, Grazzi (2010) finds that being a female reduces the probability of Internet use and use at home in up to 14%, even controlling for other factors. In a study for Chile and Mexico, countries with significant gender digital divides, Sánchez (2010) observes smaller effects of being a female on the probability of Internet use. The study also notices that the marginal effect of income on the probability of Internet use is smaller for females than males. Finally, Hilbert (2010) presents evidence for a large group of Latin American countries suggesting that the gender digital divide in the developing world is explained by the unfavorable conditions of women versus men with respect to education, employment and income.

3. Data and main patterns

Before turning to the empirical approach, this section shows the main patterns of the gender differences in Internet use and access in the different countries considered. The data used in this study comes from recent National Household Surveys in six Latin American countries, namely, Brazil and Costa Rica (2005), Chile (2006) and Honduras, Mexico and Paraguay (2007). Except for the case of Mexico, where the data are from an *ad-hoc* ICT survey, the information comes from regular household surveys which include ICT related questions. All the surveys are representative at national level and contain household and individual level information for many variables like position in household, age, education, income, labor market status, occupation, sector of activity, etc. Table V.1 gives details on data sources.[6]

Table V.1
National household surveys description

Country	Year	Survey	Institution
Brazil	2005	Pesquisa Nacional por Amostra de Domicílios (PNAD)	Fundacao Instituto Brasileiro de Geografia e Estatistica (IBGE)
Chile	2006	Encuesta de Caracterización Socioeconómica Nacional (CASEN)	Ministerio de Planificación Nacional (MIDEPLAN)
Costa Rica	2005	Encuesta de Hogares de propósitos múltiples (EHPM)	Instituto Nacional de Estadística y Censos (INEC)
Honduras	2007	Encuesta Permanente de Hogares de Propósitos Múltiples (EPHPM)	Instituto Nacional de Estadística (INE)
Mexico	2007	Encuesta Nacional sobre Disponibilidad y Uso de las Tecnologías de la Información en los Hogares (ENDUTIH)	Instituto Nacional de Estadística y Geografía (INEGI)
Paraguay	2007	Encuesta Permanente de Hogares (EPH)	Dirección Nacional de Estadísticas, Encuestas y Censos (DNEEC)

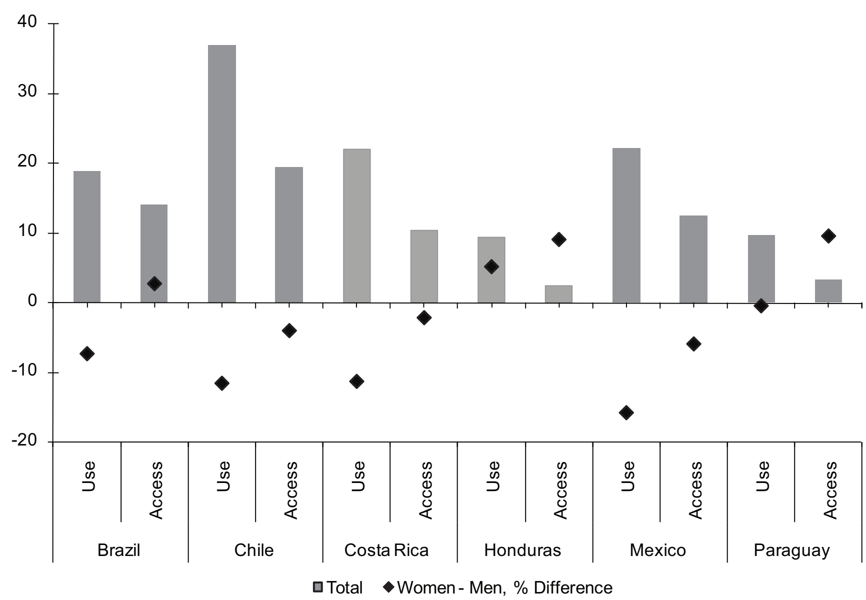
Source: Author's elaboration.

[6] More information about the data is available at the OSILAC website. The statistics presented in this section were obtained using appropriate weight factors to make them representative at the country level.

(a) Gender differences across demographic and socio-economic groups characteristics

Figure V.1 presents the main patterns of Internet use and access for both men and women. For each country, the bars represent the percentage of the population who use Internet -regardless of points of access- and have Internet access at home. In order to explore the extent of gender differences the dots show the percentage difference between the fraction of women and men in each category. Besides the gender discussion, there is significant heterogeneity in the access and use of Internet across countries (see Figure V.1). There are also important differences between use and access within countries. That is, while in Honduras and Paraguay Internet use is around three times more prevalent than Internet access, in Brazil the fraction of people who use the Internet is only around 35% greater than the fraction of the population with Internet access at home.

Figure V.1
Patterns of Internet use and access
(Percentages)

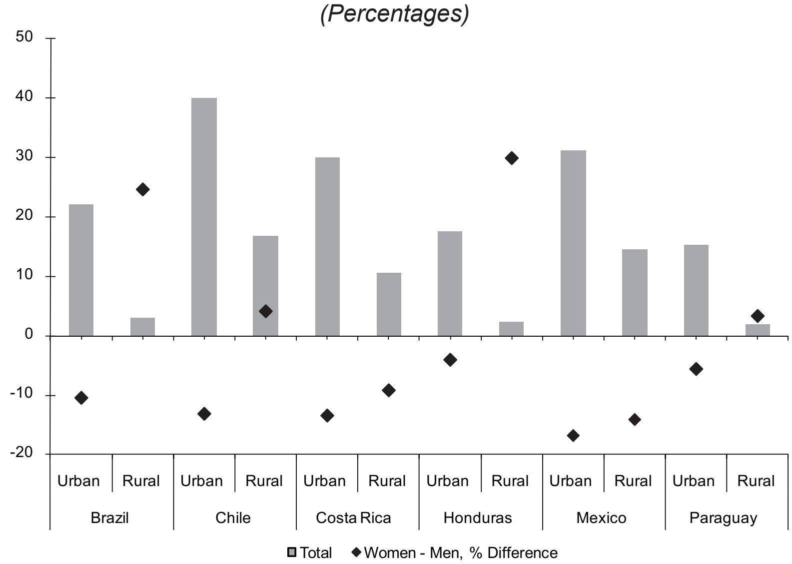


Source: Authors' elaboration based on National Household Surveys.

There are also wide dissimilarities across countries regarding gender differences in Internet use and access. On the one hand, it is observed that an equal or higher fraction of women than men access and use Internet in Honduras and Paraguay, the countries with the lowest levels of Internet prevalence in the sample. On the other hand, in Brazil, Mexico, Chile and Costa Rica, the fraction of users among men is between 7 and 16% higher than the counterpart fraction of women. When considering access instead of use, it is noted that all these differences are reduced or even reversed, like in the case of Brazil. This pattern arises as a result of a household composition effect; it indicates that there are women who can potentially use the Internet (because they have access at home) but for different reasons (household time allocation decisions, preferences, skills, etc.) they do not do it.

Additionally, it is interesting to explore the gender digital divide in Internet use among other dimensions like geographic area, income distribution, age, education, labor status and employment category. Figure V.2 presents data on the fraction of Internet users according to area of residence. Confirming the results of previous studies, Internet use in urban areas is far more common than in rural areas across countries. This is a result of infrastructure restrictions to access and different characteristics of the population in rural areas. Paraguay, Brazil and Honduras are the countries with the greatest urban *vs.* rural relative inequalities in Internet usage. What is remarkable is that while there is evidence of a gender difference in Internet use against women in urban areas, the difference applies to all countries and is significantly smaller and in some cases even reversed in rural districts. Moreover, in four countries there is a digital divide against men in rural areas (see Figure V.2). These patterns probably help to explain the small gender differences in Internet use in Honduras and Paraguay emerging from Figure V.1, since both are countries with large rural areas.

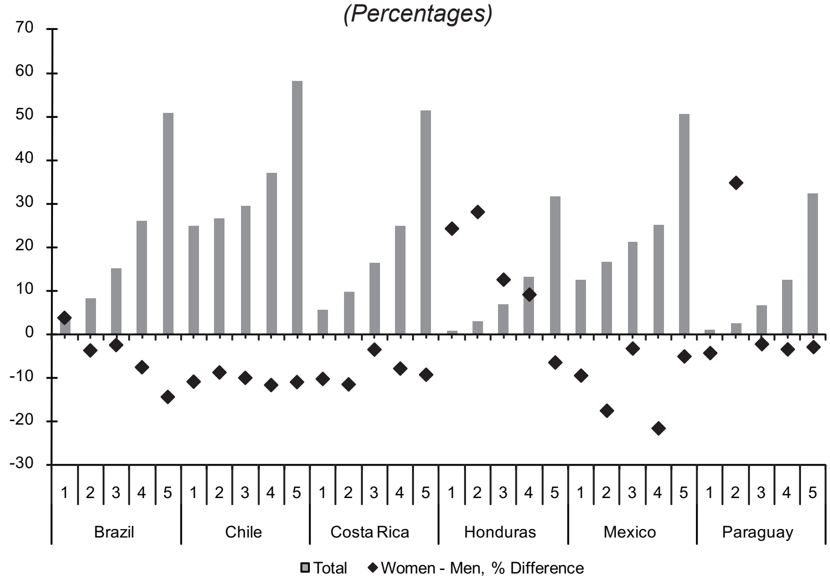
Figure V.2
Internet use by rural-urban areas
(Percentages)



Source: Authors' elaboration based on National Household Surveys.

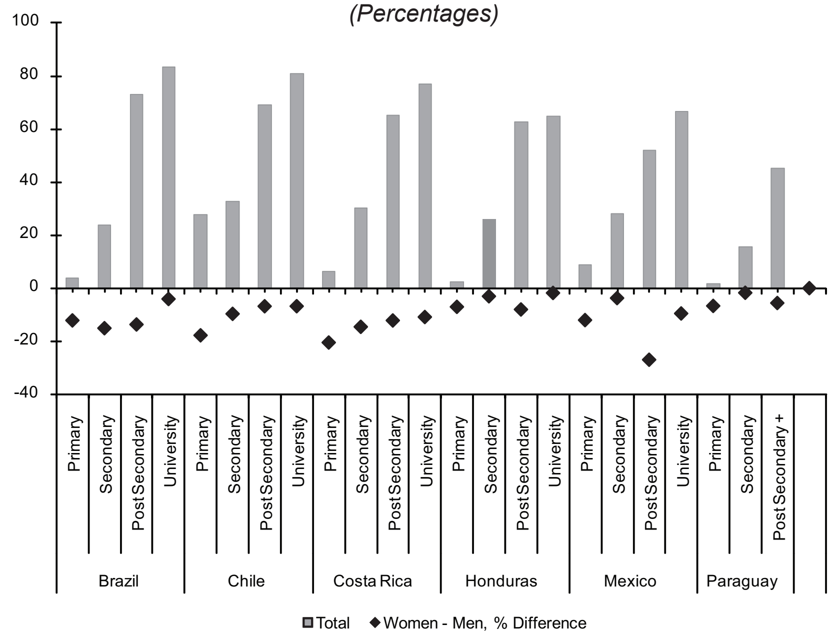
There is substantial evidence of a strong positive correlation between Internet use and income. The information presented in Figure V.3 is consistent with this evidence and shows that the intensity of Internet usage is increasing with household income quintiles in all countries. This trend is particularly strong in Honduras, Paraguay and Brazil where the rates of Internet use among the fifth quintile is at least 14 times higher than the corresponding for the first quintile. The country with the lowest inequality in use by income is Chile. Despite this result, there is not a common relationship between gender differences in Internet use and income quintile for all countries. Notwithstanding, it seems to be the case that in general the gender digital divide against women is more frequent in the highest quintiles of the household income distribution. Even in countries like Brazil, Honduras and Paraguay, a greater percentage of women than men use the Internet in the lowest income quintiles. Given the positive association between education and income, it is not surprising to find higher Internet use rates for people with higher education levels in all countries. This is what comes out from Figure V.4 which displays the corresponding data for groups classified according to the highest attained education level. The gender differences in Internet use rates consistently favor men across all formal education categories in all countries.

Figure V.3
Internet use by quintile of household income
(Percentages)



Source: Authors' elaboration based on National Household Surveys.

Figure V.4
Internet use by educational groups[a]
(Percentages)

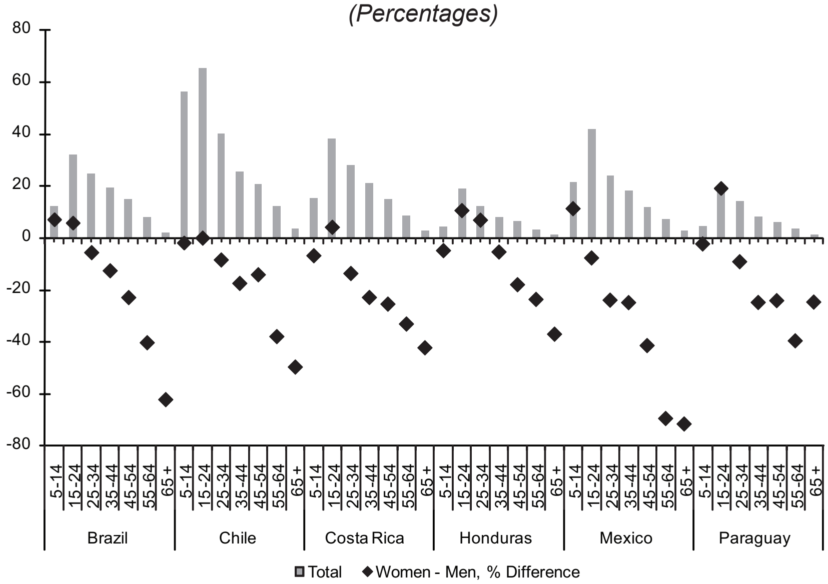


Source: Authors' elaboration based on National Household Surveys.
[a] *Data for Paraguay is not available for individuals with university and postsecondary education separately.*

Figure V.5 shows Internet use rates and the related gender disparities by age groups. It is interesting to note that for all the countries surveyed, the rates of Internet use are greater for women in at least one of the groups of people under 24 years old. The continuation of this demographic aspect of Internet use over time would then imply a trend towards the disappearance of digital inequalities, at least in the use versus not use dimension. Turning to a different perspective, Figure V.6 reports the percentage of Internet users for three groups of individuals classified according to their labor market status: employed workers, unemployed workers and students. Several results must be emphasized. First, the data show similar rates of Internet use for employed and unemployed workers but higher rates for students. This occurs because students are presumably younger and they are more likely to use Internet (see Figure V.5). Second, employed women consistently present significantly higher rates of Internet use than men in the six countries under analysis. Third, this trend is maintained when looking at the use rates for the unemployed in all countries but Mexico and Brazil, where unemployed women exhibit lower Internet use rates than men.[7] Fourth, there are similar rates of Internet use for men and women among students.

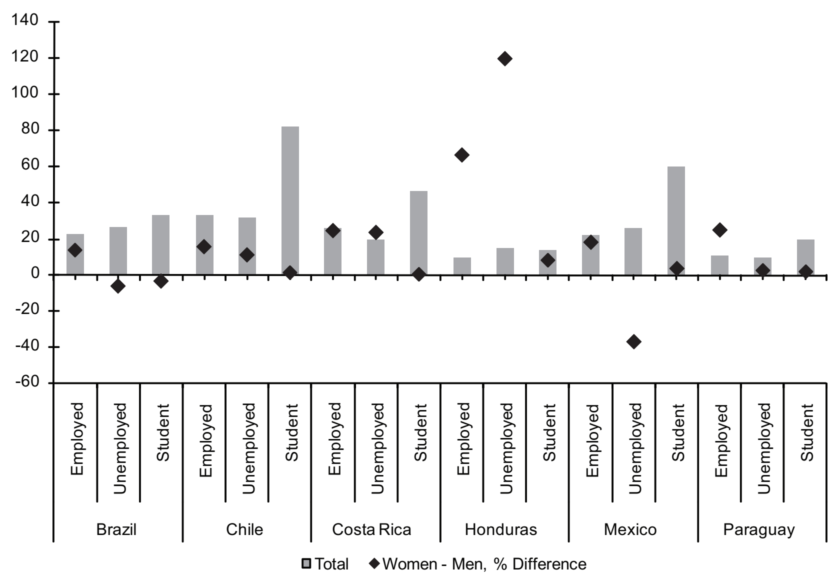
[7] The case of Mexico is particularly striking, where the use rates for unemployed women is 37% lower than the Internet use rate for unemployed men.

Figure V.5
Internet use by age group
(Percentages)



Source: Authors' elaboration based on National Household Surveys.

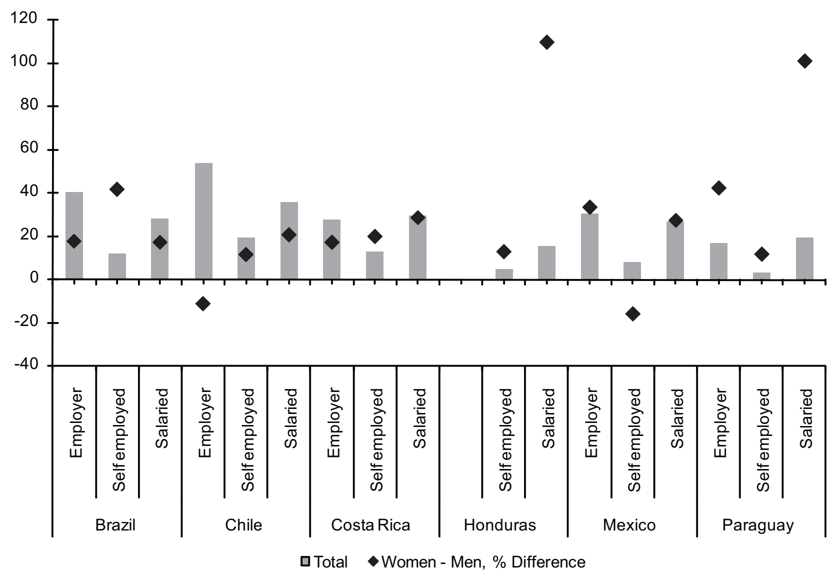
Figure V.6
Internet use by labor market status
(Percentages)



Source: Authors' elaboration based on National Household Surveys.

Finally, Figure V.7 disentangle Internet use rates for the following categories of employed workers: employer, salaried employee and self employed. The data exhibit similar or slightly higher Internet use rates for employers than for wage workers in all countries, and significantly lower rates for the self employed. Interestingly, when considering gender differences, a much greater rate of Internet use among women than men in all employment categories is observed.[8] This pattern is more pronounced among salaried workers, explaining the "advantage" of employed women in Internet use relative to men reported in Figure V.6.

Figure V.7
Internet use by employment category
(Percentages)



Source: Authors' elaboration based on National Household Surveys.

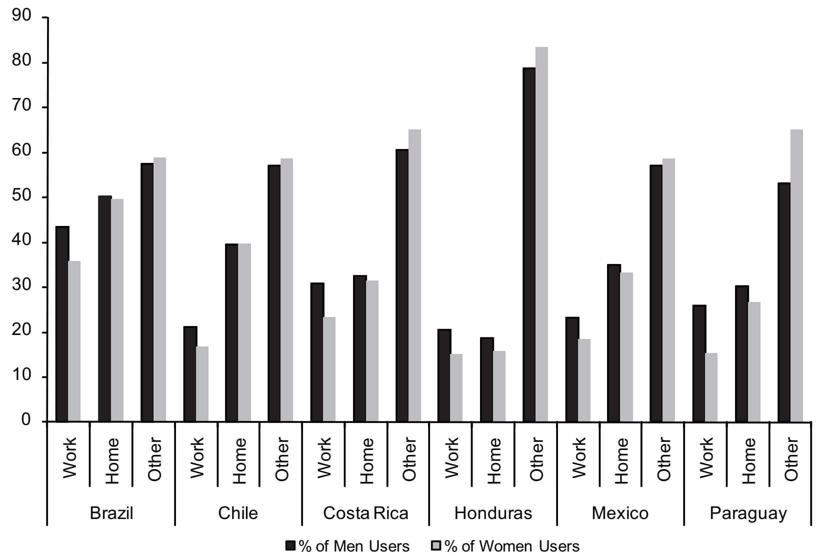
(b) Gender differences in points of access and types of Internet applications

Figure V.8 reports the percentages of male and female Internet users who access the web at work, at home and at other points of access like communal and education centers, cybercafés, etc. The three categories are not exclusive; that is, it can be the case that a user is in all three categories at the same time. In all the countries examined, at least half of users access the Internet in common access places compared with much lower fractions of accesses at home and work. It is interesting to note that the patterns of

8 The only two exceptions are employers in Chile and self employed workers in Mexico.

gender differences in fractions of users in the three categories are quite consistent across countries. Indeed, it is observed that there is a higher fraction of users at work among male than female users (see Figure V.8). This is probably a result of the lower labor force participation rates among women. Also, there are no relevant differences between male and female users accessing Internet at home. Finally, female users seem more likely to get into the Internet from other common access points than men, as the fraction of accesses in the category “Other” is greater for women than men for all countries.

Figure V.8
Internet use by point of access
(Percentages)



Source: Authors’ elaboration based on National Household Surveys.

Table V.2 gives and idea about what male and female do when they surf the web. There are five categories of applications: Entertainment, Search of Information, Communication, Commerce and Education. Table V.2 displays the percentages of individuals reporting usage in the different categories. Like in the case of Figure V.8, the categories are not mutually exclusive. The results suggest notable country and gender differences in Internet use by type of application. Results regarding gender differences are though similar between countries and they are in line with the international evidence mentioned in the previous section. The main results arising from Table V.2 are: i) males are more (less) likely to use the Internet for entertainment and e-Commerce (educational purposes) than females; and ii) similar fractions of males and females use the Internet for search of Information and Communication, with slightly more weight on women for the former application and men for the latter.

Table V.2
Internet use by main applications
(Percentages)

Country	Users	Entertainment	Search	Communication	Commerce	Education
Brazil	Male	74.0	23.9	68.8	16.5	68.4
	Female	67.1	25.0	68.4	10.8	75.0
Chile	Male	54.7	90.9	58.8	7.3	12.1
	Female	50.5	90.8	60.2	5.5	12.4
Costa Rica	Male	49.3	72.2	70.5	9.5	56.1
	Female	40.9	69.1	70.3	5.4	63.2
Honduras	Male	41.7	68.4	69.6	5.0	60.9
	Female	32.8	63.7	71.4	3.3	63.1
Mexico	Male	19.9	51.0	48.4	7.2	41.5
	Female	14.2	49.1	49.5	3.3	44.9
Paraguay	Male	11.0	10.3	51.8	2.3	39.7
	Female	4.9	4.6	55.7	1.2	49.3

Source: Authors' elaboration based on National Household Surveys.

4. Empirical approach

The data presented in the previous section suggest that on average there is a gender digital divide against women. It is observed that the gender digital divide is more frequent in urban rather than in rural areas; that it affects older women of all education levels and that it is more prevalent in the middle and upper ends of the household income distribution. Also, there is no evidence of a gender digital divide among employed workers. However, the information presented does not provide insights to understand to what extend gender disparities in Internet use are a result of gender differences in individuals' characteristics.

This section presents a simple model of the determinants of Internet use to analyze the effect of being a woman on the probability of using Internet controlling for different socio-demographic characteristics. In a similar way to Grazzi (2010) and Sánchez (2010), we propose a model for the probability of Internet use based on an indirect utility approach in the spirit of Fairlie (2004). In particular we estimate the following Probit specification for an individual *i* in any country:

$$\Pr(\textit{Internet Use}_i=1) = F(\alpha + \beta_0{*}\textit{Woman}_i + \beta_1{*}\textit{Log Income}_i + \beta_2{*}\textit{Age}_i + {}_3{*}\textit{Years of Education}_i + \beta_4{*}\textit{Urban Area}_i + \beta_5{*}\textit{Unemployed}_i + \beta_6{*}\textit{Student}_i + \textstyle\sum_{j=1..J}\gamma_j{*}\textit{Occupation}_i + \sum_{k=1..K}\delta_k{*}\textit{Sector}_i) \qquad (1)$$

Where *Internet Use* refers to Internet use at any place, *Log Income* is the per capita household income, *Age* and *Years of Education* refer to the age and years of formal education of the individual. All other variables are dummies that assume the value 1 if the individual is a woman, lives in an urban area, etc. The dummy variables *Unemployed* and *Student* control for the individual labor market status and are exclusive for each individual, *i.e.* an individual cannot be in all the four states. Finally, the last two sets of dummies control for occupation and sector of activity of employed individuals. We include these variables related to individuals' characteristics in the labor market because we believe they could be relevant exogenous determinants of Internet use. It would be expected for example that a worker in the financial services sector is more likely to use Internet than a worker in the agricultural sector. The reference labor market status category corresponds then to the non labor market participants who are not students.

In a study about the determinants of Internet use at home by households in Latin America, Grazzi (2010) includes Internet access at home as one of the relevant determinants of use. Given that having an Internet connection at home is a condition for using the Internet, the decision to use the Internet is related to the decision to get an Internet connection. This raises a selection problem of users among households with access that is dealt with in his study. In the case of this study where the object of analysis is Internet use at any place, the selection problem should not be important. That is, Internet access is not necessarily a prerequisite for using the Internet at any place. Indeed, the data for the six household surveys considered for this study show that the percentage of Internet users who only use the Internet at home with respect to the total number of Internet users ranges between 7% for Honduras to 25% for Chile. Another reason for excluding access in (1) is that part of its effect might be captured by *Log Income*. Anyway and regardless of minor selection problems, the coefficients in (1) should be read as conditional on having access to an Internet connection.

However, when estimating (1) with Internet Use at Home in the left hand side, we first estimate in a similar fashion to Grazzi (2010) the following selection equation,

$$\Pr(\textit{Internet Access at Home}_i = 1) = F(\gamma + \delta_0 {*} \textit{Income}_h + \delta_1 {*} \textit{Education Household}_h + \delta_2 {*} \textit{FamilySize}_h + \delta_3 {*} \textit{Economic Activity}_h + \delta_4 {*} \textit{Student density}_h + \delta_5 {*} \textit{Urban}_h) \qquad (2)$$

Where *h* denotes a household. Equation (2) considers several household level variables as determinants of Internet adoption.[9] $\textit{Income}_h$ refers to household income, $\textit{Education Household}_h$ is the average years of education in the household; $\textit{Family Size}_h$ is the number of household members; $\textit{Economic Activity}_h$ represents the fraction of household members aged between 15 and 65 years old; $\textit{Student density}_h$ is the fraction of members who are students and $\textit{Urban}_h$ is a dummy assuming a value of 1 if the household is in urban areas

[9] We are not controlling for the selection of Internet access among those households with a computer. The analysis assumes then a perfect correlation between having a computer at home and having access to the Internet. Grazzi and Vergara (2010) address the selection problem of PC ownership among those with an Internet connection.

and 0 otherwise. After estimating (2) we compute the *Inverse Mills Ratio*, defined as the ratio between the predicted density and the predicted cumulative distribution function, and add it as an explanatory variable for Pr(*Internet Use at Home*$_i$=1) in equation (1).

The results presented in the next section are based on marginal effects estimations evaluated at the means of the corresponding independent variables. The marginal effects are interpreted as the change in the probability of Internet use for an infinitesimal change in each of the continuous variables in (2) and the discrete change in that probability for the dummy variables case. Then, the coefficient for women for example indicates the impact of being a woman on the probability of using the Internet controlling for other characteristics. That is, if this coefficient is negative women are less likely to use the Internet than men no matter their education level, occupation, sector of activity, etc. This estimated coefficient can be a result of use discrimination or of the effect of unobserved and/or omitted variables in the model. The inclusion of a large set of dummies in (1) would reduce though major potential omitted variable problems.

We estimate different variations of our basic specification. We start by estimating equation (1) using the whole sample of individuals for each country's survey. We then restrict our sample only to heads of households in order to inquire whether there are any gender related differences in the probability of Internet use among households' heads of similar characteristics. Third, we estimate (1) considering the determinants of Internet at work by employed workers in which we consider the individual wage (*Log Wage*) instead of households' per capita income among the explanatory variables. We also consider two separate specifications for the determinants of Internet use at any place by the unemployed workers and students. Given the sample definitions, these last two models do not include the labor market status as well as the occupation and sectorial dummies in (1). Finally, we estimate (1) using Internet use at home as dependent variable controlling for the selection equation (2). We believe that this set of specifications help to identify whether there is any gender bias in the determinants of Internet use that are not related to other individuals' characteristics.

5. Results

Tables A.2 to A.6 in the appendix display the econometric results for different estimations of (1) for each country. The second column presents the result of the estimation of (1) for the whole sample and, as explained in the previous section, the rest of the columns report the results for a sample of household heads, employed workers, unemployed workers and students, respectively. Similarly, Table V.3 and V.4 present the estimation results for the determinants of Internet use at home controlling for the sample selection problem. The coefficients reported are marginal effects. All the estimation results confirm the finding of previous studies (Grazzi, 2010; Sánchez, 2010) in the sense that earning a higher income or wage, being younger, having more years of education and living in urban areas all increase the probability of Internet use. In all the cases the marginal effects are statistically significant at the 1% level. Additionally, the labor market status dummies indicate that students and the unemployed tend to have a higher probability of Internet use compared with the rest of individuals who are not in the labor force, *ceteris paribus*. It should be mentioned that the estimations for the samples containing employed workers include a set of occupation and sector of activity dummies which are not reported in the tables.[10]

Table V.3

Determinants of Internet use at home with sample selection correction: marginal effects

Variables	Brazil	Chile	Costa Rica	Honduras	Mexico	Paraguay
Woman	-0.057	-0.051	-0.054	-0.052	-0.039	-0.058
	(0.005)***	(0.008)***	(0.020)***	(0.022)**	(0.035)	(0.044)
Log Income	0.168	0.095	0.143	0.122	0.108	0.283
	(0.008)***	(0.013)***	(0.034)***	(0.023)***	(0.040)***	(0.127)**
Age	-0.006	-0.009	-0.008	-0.007	-0.017	-0.007
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Years of Education	0.052	0.002	0.024	0.063	0.049	0.064
	(0.001)***	(0.001)**	(0.008)***	(0.003)***	(0.004)***	(0.009)***
Urban Area	0.178	0.220	0.098	0.116	0.108	0.045
	(0.028)***	(0.035)***	(0.034)***	(0.102)	(0.052)**	(0.172)
Unemployed	0.257	0.130	-0.102	0.104	0.028	not included
	(0.007)***	(0.024)***	(0.102)	(0.081)	(0.094)	
Student	0.390	0.171	0.230	0.345	0.312	0.253
	(0.012)***	(0.014)***	(0.036)***	(0.038)***	(0.043)***	(0.045)***
Inverse Mills Ratio	0.231	-0.000	0.064	0.184	0.07	0.353
	(0.013)***	(0.022)	(0.046)	(0.704)***	(0.063)	(0.143)**
Observations	48 690	24 306	2 995	2 415	2 044	651
Pseudo R2	0.414	0.1801	0.2205	0.2281	0.3211	0.3418

Source: Author's own elaboration.
*Note: Robust standard errors clustered at the household level in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively. All regressions include a correction for sample selection and dummies for occupation and sector of activity.*

[10] *A detail of these categories is presented in Table A.1 in the Appendix.*

Table V.4
Determinants of Internet use at home with sample selection correction: marginal effects
Type of occupation and sector of activity dummies not considered

Variables	Brazil	Chile	Costa Rica	Honduras	Mexico	Paraguay
Woman	-0.101	-0.055	-0.069	-0.068	-0.051	-0.097
	(0.005)***	(0.007)***	(0.016)***	(0.020)***	(0.033)	(0.040)**
Log Income	0.148	0.120	0.156	0.125	0.112	0.270
	(0.009)***	(0.013)***	(0.037)***	(0.023)***	(0.038)***	(0.117)**
Age	-0.007	-0.008	-0.009	-0.006	-0.017	-0.006
	(0.002)***	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.001)***
Years of Education	0.067	0.005	0.034	0.067	0.057	0.065
	(0.001)***	(0.001)***	(0.008)***	(0.003)***	(0.004)***	(0.008)***
Urban Area	0.154	0.233	0.084	0.114	0.104	0.069
	(0.027)***	(0.034)***	(0.033)**	(0.109)	(0.052)**	(0.157)
Unemployed	0.165	0.092	-0.064	0.050	-0.049	.
	(0.012)***	(0.027)***	(0.081)	(0.086)	(0.092)	.
Student	0.338	0.135	0.177	0.346	0.289	0.304
	(0.017)***	(0.013)***	(0.026)***	(0.029)***	(0.042)***	(0.035)***
Inverse Mills Ratio	0.209	0.003	0.057	0.189	0.086	0.346
	(0.013)***	(0.023)	(0.045)	(0.040)***	(0.059)	(0.136)**
Observations	48 690	24 306	3 008	2 415	2 044	653
Pseudo R2	0.392	0.158	0.205	0.217	0.299	0.284

Source: Author's own elaboration.
*Note: Robust standard errors clustered at the household level in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively. All regressions include a correction for sample selection (coefficients not reported).*

In order to focus on the gender dimension, Table V.5 summarizes the results of the marginal effects for the dummy *Woman* in Tables A.2 to A.6 and Table V.3. As it will be seen, results show that gender disparities in the probability of Internet use are very small when controlling for individuals characteristics. Starting with the estimation of (1) for the complete surveys' sample, it is observed that the coefficient for Woman is negative in all the countries analyzed but Paraguay, where the statistic is not significantly different from zero. The marginal effects vary between -.31% in Honduras to -3.63% in Chile. They indicate that given other characteristics, the effect of being a woman in the probability of Internet use is negative but small.

The results for the countries with data on household heads (column three of Table V.5) are similar but less robust. *Ceteris paribus*, Female household heads are less likely to use the Internet than their male counterparts only in Brazil and Chile, to a lesser extent in Paraguay, and more likely in Honduras. For Costa Rica, the marginal effect is not statistically different from zero. Data for Mexico is not available to perform the exercise. These results could be interpreted as female household heads not being significantly disadvantaged with respect to other women when compared to their Internet usage prospects.

Table V.5
Summary of results: marginal effect of woman in different specifications

Population	Total	Heads of households	Employed workers	Unemployed workers	Students	Total
Dependent Variable	Internet use	Internet use	Internet use at work	Internet use	Internet use	Internet use at home
Brazil	-0.007	-0.018	0.002	-0.027	-0.001	-0.057
	(0.001)***	(0.001)***	(0.001)**	(0.010)***	(0.005)	(0.005)***
Chile	-0.036	-0.041	-0.001	0.016	0.011	-0.051
	(0.004)***	(0.005)***	(0.003)	(0.018)	(0.006)*	(0.008)***
Costa Rica	-0.016	-0.002	0.019	0.012	-0.014	-0.054
	(0.004)***	(0.008)	(0.004)***	(0.023)	(0.017)	(0.020)***
Honduras	-0.003	0.006	-0.001	0.030	-0.005	-0.052
	(0.001)***	(0.002)***	(0.001)***	(0.0175)*	(0.002)*	(0.022)**
Mexico	-0.029	not availabe	0.002	-0.030	0.026	-0.039
	(0.007)***		(0.003)	(0.018)*	(0.035)	(0.035)
Paraguay	-0.001	-0.004	-0.004	-0.006	-0.001	-0.058
	(0.002)	(0.0025)*	(0.001)***	(0.017)	(0.014)	(0.044)

Source: Author's own elaboration.
*Note: This table reproduces the marginal effect for Woman in regression results presented in Tables V.3-V.7 and Table V.8a. Robust standard errors in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively.*

As mentioned above, results in columns four, five and six of Tables A.2 to A.6 correspond to estimations of specification (1) with samples of Employed Workers, Unemployed Workers and Students, respectively. They intend to inquire about the extent of gender digital inequalities for people in similar groups. Columns four to six in Table IV.5 summarize these results. Regarding gender disparities in Internet use at work by the employed, there were no statistically significant differences found in Chile and Mexico. Interestingly, these are the countries with the greatest levels of gender differences in Internet use. In Brazil and Costa Rica, women are slightly more likely to use the Internet at work than men, while in Honduras and Paraguay the opposite is true. The magnitude of the marginal effects is in all the cases very small, and the gender effect on the probability of Internet use at work is never greater than 1%.

As indicated in Table V.5, results on the gender effects on the probability of Internet use by the unemployed are less robust in terms of their statistical significance. Indeed, only in the case of Brazil the relevant statistic is significant at the 1% level. In Chile, Costa Rica and Paraguay there are no significant gender differences in the probability of Internet use. According to the results, in Brazil and México, unemployed women are around 3% less likely to use the Internet than unemployed men of similar characteristics, respectively. Finally, in Honduras unemployed females are 3% more likely to use the Internet than their males' counterparts, ceteris paribus, but the marginal effect is significant only at the 10% level. Results based on the sample of students are even less robust as there were only obtained significant marginal effects for the variable Woman in Chile and Honduras. In Chile, female students are 1.1% more likely to use the Internet than male students, while in Honduras they situation is exactly the opposite.

Finally, results indicate greater gender differences in Internet use at home, controlling for individual characteristics. Indeed, the estimation results for the probability of Internet use at home suggest that in Brazil, Chile, Costa Rica and Honduras women are around 5% less likely to use the Internet at home even controlling for other characteristics (see last column, Table V.5). The equivalent marginal effects for Honduras and Mexico are of similar magnitudes but not statistically significant. These results indicate on average lower unexplained gender differentials in Internet use to those reported by Grazzi (2010) using a similar technique. The reasons for this divergence are in some cases the use of different datasets but mainly because of differences in the model specification. In particular, the dummies on employed workers' characteristics included in this study in some cases explain to a large extent the lower Internet usage rates by women. Indeed, Table IV.4 reports the estimation results of model (1) without controlling for employed workers' occupation and sector of activity dummies. The results are qualitatively the same as those of Table IV.3., but it is interesting to note though that for all countries, the marginal effects for women are greater in absolute terms. The most striking cases are the ones of Brazil and Paraguay, where the marginal effects for the variable Woman almost double.

6. Concluding remarks

This paper utilizes household surveys' micro data for six Latin American countries to analyze the gender role in the digital divide in Internet usage. The countries studied are Brazil, Chile, Costa Rica, Honduras, Mexico and Paraguay. The data suggest that on average there is a gender Internet use divide against women in the region. It is also observed that the gender digital divide against women is more frequent in urban rather than in rural areas; that it affects older women of all education levels and that it is more prevalent in the middle and upper ends of the household income distribution. Additionally, there is no evidence of gender inequality in terms of Internet use at work according to the data. Women are more likely to access the web from common access points than men, who are more likely to access from work. The fraction of men and women users who access at home is similar. Regarding gender differential in types of applications, women seem more interested in using the Internet for education and communication than men. Men seem instead more prone to use the web for entertainment and commerce than women. Finally, the data show that in all the countries studied the gender divide in Internet use is almost inexistent among individuals with less than 24 years old.

The econometric results indicate that controlling for different characteristics including geographic area of residence, age, education, income, labor market status, occupation and sector of activity, there is still a gender gap in Internet usage. However, its magnitude is small and it does not seem to significantly affect the probability of Internet use at any place. Notwithstanding, even controlling for the same characteristics, being a female reduces in up to 6% the probability of Internet use at home. These results, combined with descriptive statistics, suggest that the gender digital divide exists but is mainly a result of different men and women characteristics. Based on these results, it is concluded that the gender digital divide seems to be mainly a consequence of gender socioeconomic inequalities.

In terms of policy implications, these results support the idea that the gender digital divide will be reduced only as long as other significant gender gaps are tackled. As proposed by Chen (2004), a challenge for public policy is then to investigate how ICT can contribute to reduce those preexistent socioeconomic inequalities. Indeed, there is great concern by policy makers of the disadvantageous insertion of women in regional labor markets. This is reflected in low female labor force participation rates and unexplained gender earning gaps. Indeed, Hoyos and Ñopo (2010) reported unexplained gender earning gaps in the range of 9 to 27% of females' wages in Latin America. Thus, ICT- related policies aimed at facilitating labor market insertion by women in better conditions, for instance allowing working from home, would help reduce these gaps. The exploration of different policy alternatives for this matter is then a subject of further research. Moreover, the data show that among Internet users in general, women in rural areas are relatively more prone to use the Internet than those in urban areas. The development of Internet infrastructure in rural areas would then be helpful for a better insertion of women in the digital society.

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8. Appendix

Table A.1

Description of variables

Variable	Description
Internet Use	1: Yes; 0: No.
Internet Use at Home	1: Yes; 0: No.
Internet Use at Work	1: Yes; 0: No.
Internet Access at Home	1: Yes; 0: No.
Woman	1: Yes; 0: No.
Log Income	Log of Per Capita Household Income.
Log Wage	Log of Wage for Employed Workers.
Age	Years of Age.
Years of Education	Number of Years of Formal Education.
Urban Area	1: Yes; 0: No.
Employer	1: Yes; 0: No.
Salaried Worker	1: Yes; 0: No.
Unemployed	1: Yes; 0: No.
Student	1: Yes; 0: No.
Sector of Activity *(aggregation of categories may differ across countries)*	1, Agriculture, hunting and forestry; 2, Fishing; 3, Mining and quarrying; 4, Manufacturing; 5, Electricity, gas and water supply; 6, Construction; 7, Wholesale and retail trade; repair of motor vehicles/ motorcycles and personal and household goods; 8, Hotels and restaurants; 9, Transport, storage and communications; 10, Financial intermediation; 11, Real estate, renting and business activities; 12, Public administration and defense; compulsory social security; 13, Education; 14, Health and social work; 15, Other community, social and personal service activities; 16, Activities of private households as employers and undifferentiated production activities of private households; 17, Extraterritorial organizations and bodies;18 Other activities, 99, Unknown; 19, Agriculture, hunting, forestry and fishing; 20, Manufacturing, electricity, gas and water supply; 21, Education, health and social services; 22, Wholesale and retail trade; repair of motor vehicles, motorcycles, hotels and restaurants; 23, Financial intermediation, real estate, renting and business activities; 24, Community, social and personal services.
Occupation	1, Legislators, senior officials and managers; 2, Professionals; 3, Technicians and associate professionals; 4, Clerks; 5, Service workers and shop and market sales workers; 6, Skilled agricultural and fishery workers; 7, Craft and related trades workers; 8, Plant and machine operators and assemblers; 9, Not qualified workers; 10, Armed Forces; 11, Other activities; 99 Unknown.

Source: Author’s own elaboration.

Table A.2
Determinants of Internet use (marginal effects): Brazil (2005)

Population	**Total**	**Heads of households**	**Employed workers**	**Unemployed workers**	**Students**
Dependent variable	Internet use	Internet use	Internet use at work	Internet use	Internet use
Woman	-0.007	-0.018	0.002	-0.027	-0.000
	(0.001)***	(0.001)***	(0.001)**	(0.010)***	(0.005)
Log income	0.091	0.063		0.202	0.264
	(0.001)***	(0.001)***		(0.006)***	(0.003)***
Log wage			0.052		
			(0.001)***		
Age	-0.002	-0.003	-0.002	-0.007	-0.000
	(0.001)***	(0.000)***	(0.000)***	(0.004)	(0.000)
Years of education	0.004	0.003	0.001	0.005	0.004
	(0.0001)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Urban area	0.064	0.040	0.026	0.112	0.206
	(0.001)***	(0.002)***	(0.002)***	(0.019)***	(0.006)***
Unemployed	0.353	0.107			
	(0.009)***	(0.020)***			
Student	0.342	0.121			
	(0.017)***	(0.029)***			
Observations	371 809	115 125	176 124	19 643	53 756
Pseudo R2	0.406	0.463	0.423	0.224	0.274

Source: Author's own elaboration.
*Note: Robust standard errors clustered at the household level in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively. The first three regressions inlcude dummies for occupation and sector of activity.*

Table A.3
Determinants of Internet use (marginal effects): Costa Rica (2005)

	Total	**Heads of households**	**Employed workers**	**Unemployed workers**	**Students**
Dependent variable	Internet use	Internet use	Internet use at work	Internet use	Internet use
Woman	-0.016	-0.002	0.019	0.012	-0.014
	(0.004)***	(0.008)	(0.004)***	(0.023)	(0.017)
Log income	0.116	0.078		0.080	0.201
	(0.004)***	(0.004)***		(0.016)***	(0.014)***
Log wage			0.05		
			(0.003)***		
Age	-0.001	-0.000	-0.000	-0.007	-0.031
	(0.000)***	(0.000)*	(0.000)	(0.000)***	(0.003)***
Years of education	0.005	0.003	0.001	0.009	0.120
	(0.000)***	(0.001)***	(0.000)***	(0.004)**	(0.005)***
Urban area	0.081	0.038	0.02	0.078	0.211
	(0.005)***	(0.006)***	(0.003)***	(0.021)***	(0.018)***
Unemployed	0.114	0.164			
	(0.023)***	(0.074)**			
Student	0.390	0.630			
	(0.016)***	(0.086)***			
Observations	39 805	11 430	17 240	942	5 752
Pseudo R2	0.352	0.425	0.384	0.189	0.296

Source: Author's own elaboration.
*Note: Robust standard errors clustered at the household level in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively. The first three regressions inlcude dummies for occupation and sector of activity.*

Table A.4

Determinants of Internet use (marginal effects): Honduras (2007)

Population	Total	Heads of households	Employed workers	Unemployed workers	Students
Dependent variable	Internet use	Internet use	Internet use at work	Internet use	Internet use
Woman	-0.003	0.006	-0.000	0.030	-0.005
	(0.001)***	(0.002)***	(0.000)***	(0.017)*	(0.002)*
Log income	0.021	0.013		0.034	0.041
	(0.000)***	(0.001)***		(0.009)***	(0.002)***
Log wage			0.002		
			(0.000)***		
Age	-0.001	-0.00	-0.000	-0.003	-0.005
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***
Years of education	0.012	0.007	0.001	0.027	0.028
	(0.000)***	(0.000)***	(0.000)***	(0.002)***	(0.001)***
Urban area	0.027	0.013	0.002	0.036	0.056
	(0.001)***	(0.002)***	(0.000)***	(0.020)*	(0.004)***
Unemployed	0.011	0.030			
	(0.005)**	(0.014)**			
Student	0.056	0.070			
	(0.003)***	(0.022)***			
Observations	75 063	17 375	28 665	1 085	24 932
Pseudo R2	0.399	0.397	0.442	0.292	0.417

Source: Author's own elaboration.
*Note: Robust standard errors clustered at the household level in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively. The first three regressions inlcude dummies for occupation and sector of activity.*

Table A.5

Determinants of Internet use (marginal effects): Mexico (2007)

Population	Total	Heads of households	Employed workers	Unemployed workers	Students
Dependent variable	Internet use	n.a	Internet use at work	Internet use	Internet use
Woman	-0.029		0.002	-0.030	0.026
	(0.007)***		(0.003)	(0.018)*	(0.035)
Log income	0.049			0.032	0.094
	(0.005)***			(0.018)*	(0.022)***
Log wage			0.019		
			(0.003)***		
Age	-0.007		-0.001	-0.008	-0.018
	(0.000)***		(0.000)***	(0.001)***	(0.008)**
Years of education	0.025		0.004	0.024	0.082
	(0.001)***		(0.001)***	(0.006)***	(0.011)***
Urban area	0.055		0.007	0.067	0.182
	(0.009)***		(0.004)*	(0.023)***	(0.040)***
Unemployed	0.112				
	(0.022)***				
Student	0.285				
	(0.024)***				
Observations	17 452		7 760	1 198	1 994
Pseudo R2	0.401		0.416	0.423	0.179

Source: Author's own elaboration.
*Note: Robust standard errors clustered at the household level in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively. The first two regressions inlcude dummies for occupation and sector of activity.*

Table A.6
Determinants of Internet use (marginal effects): Paraguay (2007)

Population	Total	Heads of households	Employed workers	Unemployed workers	Students
Dependent variable	Internet use	Internet use	Internet use at work	Internet use	Internet use
Woman	-0.001	-0.004	-0.004	-0.006	-0.000
	(0.002)	(0.002)*	(0.001)***	(0.017)	(0.014)
Log income	0.034	0.016		0.017	0.119
	(0.002)***	(0.002)***		(0.011)	(0.010)***
Log wage			0.009		
			(0.001)***		
Age	-0.001	-0.001	-0.000	-0.003	0.021
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.003)***
Years of education	0.002	0.001	0.001	0.013	0.001
	(0.000)***	(0.000)***	(0.000)***	(0.004)***	(0.001)
Urban area	0.038	0.014	0.010	0.018	0.137
	(0.004)***	(0.003)***	(0.002)***	(0.015)	(0.017)***
Unemployed	0.035	0.002			
	(0.014)**	(0.009)			
Student	0.068	0.203			
	(0.009)***	(0.133)			
Observations	18 784	4 792	6 319	386	2 546
Pseudo R2	0.343	0.411	0.330	0.227	0.291

Source: Author's own elaboration.
*Note: Robust standard errors clustered at the household level in brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively. The first two regressions inlcude dummies for occupation and sector of activity.*

B. ICT and firm performance in Latin America

I. ICT and labor productivity in Colombian manufacturing industry

Luis H. Gutiérrez[1]

1. Introduction

The information and communication technologies (ICT) are constituted by the investments in hardware, software and communication media. The fast technological developments in the production of microprocessors and their increasingly low prices have strongly reduced the price of computers and other computing and communication equipments. This has allowed the business sector to make important disbursements for the purchase of such equipments. Researchers on the economic growth theory and the technological innovation area have been studying the relationship between investment in ICT and productivity for some decades. Due to the data availability, the first studies were focused on the existing relationship at country or industry level. Nevertheless, these studies did not show the expected positive relationship between ICT and productivity (Brynjolfsson, 1993).

The present study analyzes the relationship between ICT investments and productivity in the Colombian manufacturing industry. It uses information from the second Survey of Development and Technological Innovation (Encuesta de Desarrollo e Innovación Tecnológica - EDIT) performed in 2005. The EDIT survey asks about investment decisions on innovation and technological development, amounts invested, reasons for investing, occupation level and quality of employed personnel, financing mechanisms and loan commitments, effect of innovation, among others. Due to the fact that the EDIT did not pose questions on firm performance variables, we use complementary data from the Annual Manufacturing Survey (Encuesta Anual Manufacturera - EAM) of 2004.

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The contribution of this work is manifold. First, it is the first Colombian study that develops an econometric approach to investigate the relationship between ICT investments and productivity in the manufacturing industry. Second, by including variables related to investments, efforts in organizational changes and human capital and innovation outcomes, the study explores the hypothesis of complementarity and the impact of innovation. Finally, the data sample used covers a great number of small firms which will allow us to test the differentiating effects, by firm size, of ICT investments, organizational changes and human capital, on labor productivity. The main outcomes confirm some of the findings of the literature. First, investment in ICT and the effort in qualification of human resources affect positively the labor productivity. Second, efforts in organizational change or management apparently do not produce short-term productivity gains. Third, innovating efforts have a positive impact on productivity. Finally, the complementarity between organizational changes, human capital and ICT investments is not confirmed.

The study is organized as follows. Section 2 resumes the academic literature related to ICT investments, human capital, organizational changes and productivity. Then, Section 3 describes the EDIT database and Section 4 establishes the hypothesis and the empirical approach. Finally, Section 5 discusses the econometric results and Section 6 concludes.

2. Literature review

Since the mid eighties, the discussion dealt mainly with the "productivity paradox". Indeed, Robert Solow stated that, "*one can see the computer age everywhere except in the productivity statistics"*.[2] Indeed, during the nineties it was difficult to measure the effects of ICT and the productivity paradox became an important subject of research.[3] However, recent studies have demonstrated that the productivity paradox was the result of several factors. First, most of the analysis was implemented at an aggregated level, either macroeconomic or at industry level.[4] Second, maybe it was a consequence of case study analysis. Third, that the analysis was based on data constructed by using inappropriate deflators or non-representative samples. Finally, that the expected positive relationship between investment in ICT and productivity is more complex and/or long-term (Brynjolfsson, 1993). The following literature review focuses on published studies concerning ICT investments and its effects on productivity at firm level.

2 Quoted in Stiroh (2008, p. 360).

3 We shall use indistinctly the terms information system (IS), information technology (IT) and information and communication technologies (ICT).

4 For example, see Jorgenson and Vu (2007), O'Mahony and Vecchi (2005), Stiroh (2008), Stiroh and Botsch (2007), Basu and Fernald (2007), Inklaar and Timmer (2007), Inklaar *et al*. (2007) and Eicher and Roehn (2007).

What are the ICT and how could they affect productivity in the firm? Brynjolfsson and Yang (1996) stated that ICT includes office, calculation and accounting equipments which consists mainly of computers and it also includes communication equipment and related software and services. This definition considers the ICT as general purpose technologies because they are used by all economic activities and have dynamic technological developments (Bresnahan and Trajtenberg, 1995).[5] Due to the fact that these technologies enable the redesign of industrial processes and improve the coordination of work groups, they contribute to the technical change in firms. Generally, their adoption is based on three elements: a) economic incentives for the managers or owners of the firm to adopt these technologies, b) risks resulting from not knowing the potential performances of these technologies and problems of adjustment, management and establishment of ICT within the productive and organization processes, and c) dissemination level in the market where the firm competes, costs and complementary services of the ICT expenditures. Once a firm manager or owner invests in ICT he should expect to see cost reductions or productivity gains, however, these may not be immediate.

In the first half of the nineties several studies addressed the issue of ICT and productivity. Brynjolfsson and Hitt (1996) developed one of the first researches dealing with the effect of ICT investment on productivity at US firm level, using data from five annual surveys applied to large companies from 1987 to 1991. Their two hypotheses were that the impact of computer capital and ICT personnel is positive, and that contribution is positive even if you deduce the ICT capital and labor cost depreciation. An important feature of their work consisted in disaggregating the firm's capital in computer capital and capital of other investment goods; and to disaggregate personnel into ICT personnel and others. The authors used a Cobb-Douglas specification in which the product was measured by sales. The results suggested a positive effect of computer investment on sales, and that the performance of employed ICT personnel was relevant, which may be due to the relatively high education level of these workers. Additionally, the authors showed that the return for investments in computers is higher than the return for other type of investments.[6]

Theoretically, Milgrom and Roberts (1990, 1995) developed several models to understand the changes occurred in North American manufacturing sector with the introduction of

[5] In an evolutionary perspective, Perez (1985) presented the idea of techno-economic paradigms, which are dominated by a key factor with the following features: (1) low and decreasing costs, (2) almost unlimited offer, (3) evident potential to influence all production spheres, (4) capacity to reduce costs and change the quality of capital, work and product equipments due to its interconnection with technical and organizational innovations. The techno-economic paradigms include, among others: new efficiency concepts for the organization of production at plant level, new models of business organization and management, new innovation patterns, less work by product unit.

[6] The study discusses three relevant factors that must be considered in the analysis of ICT investment and productivity: errors in ICT equipment rating, errors in the deflators used, and understatement or wrong classification of what is considered investment in information systems.

information technologies.[7] They argued that, given an exogenous reduction in the prices of technologies, that is, CAD (Computer-aided Design) and CAM (Computer-aided Manufacturing), this reduction implied direct and indirect effects on the applicability of those technologies in the productive process. A price reduction —direct effect— promotes its use, develops the design capacity and tends to improve the production levels by reducing the marginal costs. Nevertheless, the indirect effects are even more important. These *"indirect effects tend, basically, to strengthen the direct effects, because the corresponding relationships are complements. Here, we use the term complements not only in the traditional sense of a relationship between input pairs, but also in a wider sense as a relationship between activity groups. The defining feature of these complement groups is that if the level of any of the subset of activities increases, then the marginal output of increases in any of the other activities also increases"* (p. 514). Although they studied a case related to CAD or CAM, it should be possible to infer that the equipments or computing systems may reduce the production processes and inventories, increase data communication and the product redesigning become complements.

Brynjolfsson and Hitt (2000) took the complementarity analysis to argue that *"a significant factor of the information technology value is its capacity to enable complementary organizational investments such as firm processes and labor practices"* and that those complementary investments *"produce in turn productivity increases, by reducing costs and, more important, by enabling the firm to increase the quality of the products in the form of new products or to improve intangible aspects of the existing products, such as convenience, immediate delivery, quality and variety"* (p. 24-25). This argument renewed the research concerning the relationship between ICT investment and productivity, but extended to include complementarities. For example, Black and Lynch (2001) partially tested this argument by using several databases of the US Census Office. They estimated an extended Cobb-Douglas production function with variables of labor practices, human capital and information technology dissemination. Although the results were mixed and they did not explicitly include a measure of investment in computers, it is worthwhile stressing the finding concerning the importance of human capital, which was positively associated to productivity.[8] In a related study, Caroli and Van Reenen (2001) used data of British and French companies in the eighties to investigate the determinants of organizational change and productivity. Interestingly, the results for the French case

[7] There are several studies that analyze the impact of ICT on productivity using data at establishment level in the United States and Canada. For the United States, see Nguyen and Atrostic (2006), Nguyen and Atrostic (2005) and Atrostic and Nguyen (2002). For Canada, see Sharp (2006).

[8] Greenan *et al.* (2001) carried out a similar analysis with a sample of French medium and large firms for the period 1986-1994. The authors used as ICT variable what they called investment in computerization, which is the proportion of the gross value of the office assets and hardware in relation to the gross value of total physical assets. They employed four measures of human capital, emphasizing the number of ICT employees and employees in R&D activities. The results depend on the adopted models. While cross-section estimations shows significant positive correlations between IT investment, human capital and productivity, panel data estimations reveal no relevant correlations.

showed that new labor practices increase productivity only if the firm have implemented other activities or have invested in complementarity assets, a result in the line of Black and Lynch (2001).

In the context of US firms, Bresnahan *et al.* (2002) developed research by explicitly considering complementarities between ICT investments, organizational changes and human capital in the production function. The correlation analysis shows that organizational changes are strongly correlated with human capital and information systems, and that investment in information systems are correlated with human capital. The first estimations suggest that both organizational change and human capital predict the demand for information systems correctly, although they are weak explanatory factors of the demand for other investment goods. In a second set of estimations, results reveal that the different information system investments are determinant factors of the human capital level. Finally, the authors analyzed the joint effect of the three inputs on productivity. The evidence suggests the existence of complementarities between investment in information systems, human capital and organizational changes.

Brynjolfsson and Hitt (2003) investigated the relationship between investment in computers and productivity for a sample of very large US companies. They stated that *"long-term benefits of computerization alone exceed the short-term contribution"* (p. 793). This would explain why some previous studies at firm level found a low or null relationship. With a database for eight years for a sample of four thousand firms, the authors discovered that investment in computers is positively correlated to productivity growth. Moreover, they fond that "*the estimated coefficient increases monotonically and substantially as you move from one year differences specifications to seven years differences specifications"* (p. 798).[9] Bertschek and Kaiser (2004) analyzed the relationship between ICT investments, productivity and organizational changes, controlling by investment in other capital assets. Their main argument is that labor productivity may be affected by ICT and non-ICT investments and organizational changes, but the relationship is bidirectional. The hypothesis is that labor reorganizations, such as hierarchy reduction within a firm and team work strengthening, act as a change parameter of the production function. The results show a positive relationship between productivity and ICT investments. The evidence also suggests that workplace reorganizations induce an increase in productivity that is attributable to complementarities with input factors.[10]

9 Zwick (2003) also studied the dynamic effects of ICT investments. For this purpose, he used panel data in the US for the period 1997-2001. By using OLS, the author found a small effect of ICT investments on productivity. The author argues that this result may be due to unobserved heterogeneity and endogeneity. A new round of estimations, controlling for both problems, shows a positive and significant impact of ICT investments on productivity.

10 Hempell (2005) used a sample of German firms for the period 1994-1999 to study how different econometric approaches produced "potentially" different results. The evidence obtained is indeed ambiguous and not robust to different specifications. However, the results also suggest that qualified human capital is a prerequisite for the ICT to have a positive effect on productivity.

More recently, several studies evaluate the relationship between IT and productivity, controlling by complementary factors. For instance, Arvanitis (2005) develops the same work of Bresnahan *et al.* (2002) for a sample of Swiss firms. The author studies the relationship between productivity and ICT investment but resulting from organizational changes and human capital variables. One of the new aspects of the survey is that it uses different measures of ICT inputs. In particular, the author used the proportion of employees connected to the Internet and Intranet. The estimations show that all variables —except the variable that measures intensity of ICT investment— are positively correlated to productivity. The organizational variables present similar results, but its relation with productivity is less robust than for ICT variables. Likewise, the results concerning human capital are the expected ones; its impact is higher than that of the organizational changes, but lower than the ICT inputs. Additionally, the author finds evidence for the complementarity hypothesis only between ICT inputs and human capital.

Gargallo-Castel and Galve-Górriz (2007a) investigates the situation in Spanish firms and adopt three main hypotheses: ICT investment *per se* does not generate any productivity gain; its effect will be positive only if it is combined with a high qualification level of the employees; and it will be higher in firms where management has proactive attitudes towards ICT investments. Indeed, they propose that firms that combine ICT with process innovation will obtain higher productivity. The econometric results reveal that: i) the effect of the ICT investment is lower than investment in other goods, ii) the interactions of the ICT variable with human capital variable and management attitude variables are always positive and relevant and iii) the interaction between ICT and the variable of investment in process innovation is not significant. Also considering Spanish firms, Badescu and Garcés-Ayerbe (2009) estimate the impact of ICT investment on labor productivity for a panel of 341 medium and large firms during 1994-1998. The results show an elasticity of 0.9%, implying that IT investment is a determinant factor of productivity growth in Spain.[11]

Giuri *et al.* (2008) study the relationship between ICT adoption, human capital, organizational changes and productivity in Italy for the period 1995-2003. Due to the panel data availability, the authors use least squares and fixed effect estimations. The evidence using least squares show a positive relationship between ICT capital stock and productivity, but negative relationships in the inter-relations of ICT investment and human capital and organizational change. The results are worse considering the dynamic effects, and only the interaction between ICT and human capital is positively associated to productivity. The interaction between IT, human capital and organizational change is negatively associated to productivity. Given that the sample of firms is basically composed by small and medium size enterprises (SMEs), this leads the authors to declare that

[11] In developing countries, the empirical evidence is scarce. One exception is Chowdhury (2006), who examined the situation in both Kenya and Tanzania. Surprisingly, the productivity outcomes show that it relates negatively to ICT investments. Chowdhury argues that this result may be explained as an excessive ICT investment or disarrangement in the relationship technology-human capital. Also, this result could be due to the fact that ICT investments take time to materialize its effect on productivity.

"in the SMEs there is a limited scope for obtaining productivity gains associated to the simultaneous adoption of different complementary strategies".

Koellinger (2008), using data for 25 European countries, analyze the determining factors for the new technologies and innovative activities to succeed. The results were the expected ones: all types of innovations are positively associated to performance variables (employment, sales and rate of return). Nevertheless, there are differences concerning product and process innovations. The former are associated positively to the rate of return and sales, while the latter do not relate positively to productivity and they relate negatively to the decreasing employment. The author explains this by arguing that process innovations are defensive strategies to maintain market shares, while product innovations are offensive strategies to capture new markets.

Overall, the literature on productivity and investment in ICT allows us to conclude some key facts. First, most of the studies show a positive, sizeable and significant impact of ICT investments on productivity. However, it is important to mention that this literature refers mainly to medium and large firms. Second, the literature also includes other factors that may boost the impact of ICT investments or that may be complementary. Indeed, the empirical studies show that, although it is possible to consider a positive impact of ICT investment, this impact holds even controlling by complementarities between human capital, organizational changes and innovations. Finally, the ICT impact on productivity is positive and relevant for most of the cross-section studies, but the outcome is less robust for panel data analysis. Although the theoretical perception and Brynjolfsson and Hitt (2003) show that lagged impacts of ICT must be positive, the few studies which used static and dynamic panel data have mixed results (Hempell, 2005; Giuri *et al*., 2008). In this perspective, it is essential to generate much more panel databases to test whether ICT investments —and its potential complementarities with human capital and organizational change— affect productivity in a dynamic pattern.

3. The Development and Technological Innovation Survey 2005

The National Planning Department (Departamento Nacional de Planeación - DNP), and the Colombian Institute for the Development of Science and Technology "Francisco José de Caldas" (COLCIENCIAS), carried out the first Survey on Technological Development (EDT) in the Colombian manufacturing sector. The survey was implemented in 1996 to 885 industrial establishments with more than 20 employees, and it was representative of the universe of 4,501 industrial establishments.[12] One key characteristic is that the most frequent innovation activity undertaken by industrial firms was the acquisition of capital-

[12] The DANE reports that in 1995, the number of industrial establishments was 7,909. A firm may have one or more establishments.

embodied technologies, followed by product and process designs. In fact, investment in capital-embodied technologies was more than 3 times higher than investment in other type of innovations and 25 times higher than the R&D investments.

Nine years later, the DNP, COLCIENCIAS and the National Statistical Administrative Department (Departamento Administrativo Nacional de Estadística - DANE) implemented a second Survey on Development and Technological Innovation (EDIT)–which is the primary database of this study. The survey was answered by approximately six thousand firms in 2005.[13] A crucial difference between EDIT and EDT is that the former considers the universe of Colombian manufacturing firms and the latter considers only a representative sample. DANE provided an EDIT database composed by 6,106 firms. Table VI.1 displays the size distribution of firms. As it may be noticed, 64% of the firms have less than 50 employees. The participation of medium and large firms represents the remaining 36%. This sampling distribution is relevant because, as we discussed in the previous section, most of the literature refers to medium and large firms.

The EDIT 2005 is composed by seven chapters. The first chapter asks if the firms invested or not in 75 development and technological innovation activities —and their respective monetary amount— during 2003 and 2004. This chapter also asks for investment decisions (answer yes or no) between product, process, organization and marketing, and the rating given to each activity. Table VI.2 displays the outcomes of investing decisions related to ICT and innovation activities in 2004.[14] Clearly, the larger the firm size, the higher seems to be the involvement in all the development and technological innovation activities (henceforth DTIA). For example, while 23% of small firms invested in ICT equipments, 41.1% of medium firms up to 100 employees invested in ICT equipment, 52.2% of medium firms up to 200 employees, 55.6% of large firms up to 500 employees and 65.2% of the very large ones. Additionally, the relevance of each activity is different. Indeed, the proportion of firms that invested in R&D is the lowest, regardless of firm size.

Table VI.1

Firm distribution by size

(Number and percentages)

Number of employees	Number of firms	%
Until 50	3 903	63.9%
51-100	959	15.7%
101-200	604	9.9%
201-500	426	7.0%
More than 500	214	3.5%
Total	6 106	100.0%

Source: Author´s elaboration based on EDIT 2005.

[13] The DANE informs that the number of firms vary between 5,950 and 6,106 according to the EDIT’s chapters. The total number of firms informed by the EAM (Annual Manufacturing Survey) was 6,847 in 2004.

[14] It must be considered that these are aggregates which take the value yes, if the firm answered yes in at least one of the items.

Table VI.2
Proportion of firms investing in ICT and innovation-related activities by size, 2004
(*Percentages and number*)

Type/Size (employees)	Until 50	51-100	101-200	201-500	More than 500
ICT equipment	23.0	41.1	52.5	55.6	65.2
Capital equipment - hardware	43.1	68.3	78.1	85.1	90.4
Management	34.1	51.1	63.1	71.3	77.0
Cross-cutting technologies	24.5	63.9	66.6	55.1	77.5
R&D	4.4	6.7	9.7	12.3	22.5
Training	41.7	61.5	73.7	80.0	83.7
Total investment	69.0	86.2	92.4	95.4	96.6
Number of firms	3 897	919	566	390	178

Source: Author´s elaboration based on EDIT 2005.

Table VI.3 displays the distribution of the invested amounts by type of activity and by firm size. In some cases, data are surprising. The most striking one shows that small firms invest a slightly higher percentage in R&D than those which have between 51 and 100 employees. This is probably a problem of the number of the reported employees or an overestimation of the total amount invested in that activity by those firms. The data of investment in training also attracts attention. Of the total amount invested in DTIA, small firms invested proportionally more in training than any other firms in 2004. On the other hand, it is not surprising that the item of investment in capital equipment and hardware appears as the most important for technological embodiment, regardless of the firm size. Likewise, monetary investments in R&D activities are minimal in all firm sizes, which corroborate the scarce effort in R&D activities. A similar result was obtained in the EDT of 1996.

Chapter II of the EDIT asks about the characteristics of the firm personnel in 2004 and also for the average labor cost according to different areas or departments.[15] Table VI.4 shows how the personnel were distributed according to education levels and firm size. Interestingly, the proportion of personnel for small firms with a doctorate is higher than the proportion for medium and large firms. In general, data shows that the personnel are distributed in a more or less homogenous way along the different firm sizes. The highest number of employees, regardless of firm size, has an education level which does not exceed the secondary education.

[15] The EDIT requested information on the personnel according to the type of contract with the firm (permanent, temporary and owner) and by area (administration, sales, design, engineering, R&D, production, quality and trials, environment, occupational health, informatics and systems and others). Chapter II also requested a depiction of personnel by educational levels: doctor, master, specialization, professional, professional trainee, technologist, technician, SENA apprentice, secondary and primary education.

Table VI.3
ICT and innovation-related investments by firm size, 2003
(Percentages)

Type/Size (employees)	Until 50	51-100	101-200	201-500	More than 500
ICT equipment	7.98	9.02	9.33	8.32	6.81
Capital equipment - hardware	35.52	45.07	50.15	51.39	54.40
Management	24.15	19.49	19.25	19.84	16.15
ICT	11.21	10.36	8.82	6.66	7.95
Cross-cutting technologies	26.25	24.07	19.33	18.34	19.30
R&D	1.26	1.05	1.29	0.94	1.50
Training	12.84	10.33	10.00	9.49	8.66

Source: Author´s elaboration based on EDIT 2005.

Table VI.4
Firm personnel by education level and firm size, 2004
(Percentages and number)

Education/Size(employees)	Until 50	51-100	101-200	201-500	More than 500
Doctor (PhD)	0.07	0.19	0.04	0.04	0.05
Master	0.22	0.15	0.20	0.22	0.26
Specialization	1.03	1.45	1.52	1.94	2.19
Professional	12.68	10.92	11.66	11.63	12.92
Professional trainee	0.39	0.40	0.34	0.40	0.44
Technologist	6.02	5.99	5.21	6.15	5.58
Technician	9.30	7.65	8.43	8.77	8.93
SENA apprentice	1.38	1.96	2.19	2.00	2.70
Secondary education	45.81	50.36	51.07	51.32	53.04
Primary education	21.93	18.58	18.35	16.23	12.38
Other	1.18	0.95	1.00	1.30	1.53
Number of firms	3 903	924	566	391	178

Source: Author´s elaboration based on EDIT 2005.

Table VI.5 displays information concerning objectives and innovation results.[16] It is clear that firm size is a relevant factor of innovation activities (*e.g.* Cohen and Levin, 1989). In fact, 69% of the very large Colombian manufacturing firms implemented innovations in products and processes against only 41% of the small firms. Interestingly, the highest percentage of firms that did not develop any innovation corresponds to the

16 The calculation methodology of the innovation measures is explained in the empirical approach.

medium firms up to 200 employees. Finally, data suggest that product innovations were more intensively implemented than process innovation, regardless of firm size. This is interesting considering the first one as an offensive strategy for capturing new markets, and the second one as a defensive strategy to maintain market shares (Kamien and Schwartz 1982 and Koellinger 2008).

Chapter IV of EDIT asked about expenditures of DTIA investments and financial sources. This information is shown in Table V.6. It is clear that, regardless of the firm size, own funds is the basic source for financing DTIA. The second source is commercial banking, while public sector financing is important only for large companies. Finally, Table VI.7 presents two productivity measures by firm size, total sales per employee and value added per employee. As expected, productivity increased monotonically with the firm size, regardless of the productivity measure.

Table VI.5
Innovation activities by size, 2004
(*Percentages*)

Innovations/Size (employees)	**Until 50**	**51-100**	**101-200**	**201-500**	**More than 500**
0 - No innovations	30.0	20.8	18.3	11.0	15.4
1 - Process innovations	11.3	11.4	10.7	10.5	4.6
2 - Product innovations	17.8	18.5	19.6	18.6	10.9
3 - Product and process innovations	40.9	49.3	51.4	59.8	69.1
Number of firms	3 108	843	541	381	175

Source: Author´s elaboration based on EDIT 2005.

Table VI.6
Financing sources by firm size, 2003
(*Percentages and number*)

Financing source/Size (employees)	**Until 50**	**51-100**	**101-200**	**201-500**	**More than 500**
Public sector (co-financing)	1.44	3.80	3.00	4.62	6.18
Public sector (credit)	2.82	8.26	8.83	10.77	18.54
Commercial banking (credit)	12.98	20.98	25.80	29.23	42.70
External sector (credit)	0.36	0.87	1.06	0.77	2.81
Other sources	0.49	0.76	0.35	1.03	3.37
Businesses sources (other sources)	51.21	65.98	71.20	78.72	73.60
Number of firms	3 898	920	566	390	178

Source: Author´s elaboration based on EDIT 2005.

Table VI.7
Labor productivity by firm size, 2004
(Sales and value added per employee)

Productivity/Size (employees)	Until 50	51-100	101-200	201-500	More than 500
Sales per worker	15 057	67 976	158 875	404 677	1 587 539
Value added per worker	5 351	26 447	58 857	173 807	742 094
Number of firms	3 903	960	602	427	214

Source: Author´s elaboration based on EDIT 2005 and EAM 2004.

4. Empirical approach

As we mentioned before, the main database used for this study is the Survey of Development and Technological Innovation (EDIT) 2005, which is complemented with data from the Annual Manufacturing Survey (EAM) 2004. Although the EDIT comprises a total of 6,106 companies, representing the universe of small, medium and large Colombian manufacturing firms, not all EDIT's chapters contain data for the total number of firms. After checking inconsistencies and other factors concerning information availability, the estimation sample is composed by 5,900 firms.[17]

Considering the main hypotheses tested in the literature and the data availability for the Colombian Manufacturing sector, we postulate four hypotheses to test: i) *ICT investment is positively related to labor productivity*; ii) *Investments on human capital affects labor productivity positively*; iii) *Investments on organizational technologies are positively related to labor productivity* and iv) *The differentiated effect of ICT on labor productivity shall be higher for those firms that innovate in processes and/or products*. Following the literature, we use an extended Cobb-Douglas production function:

$$\mathrm{Ln}\,(Y/L) = \alpha_1\, LnStock_{NO\text{-}ICT,i} + \alpha_2\, LnStock_{ICT,\mathrm{i}} + \alpha_3\, LnL_i + \alpha_4\, LnHumanCapital_i + \alpha_5\, D\_Management_i + \alpha_6\, Innovation_i + \alpha_7\, Z_i + \varepsilon_i \qquad (1)$$

We consider two productivity measures at firm level as dependent variable: i) value added per worker and ii) sales per worker. $LnStock_{NO\text{-}ICT}$ corresponds to the value of the non-ICT capital stock and $LnStock_{ICT}$ is the ICT equipment capital stock. We calculate these two

17 Several factors reduced the firm sample. First, some firm managers did not answer certain modules of the survey. Second, not all firms reported data on the number of employees. Third, due to the fact that the EDIT did not consider any performance variable, it was necessary to ask DANE for EAM data for 2004 and 2005. However, DANE keeps confidentiality agreements even with random codes. Likewise, some firms may have not reported information to the EAM, but rather to the EDIT. Finally, with the information of the EAM-2004, additional firms were eliminated according to two criteria: firms that that did not report data on value added or sales and firms that declared to have no value in the assets account.

inputs in relation to the total number of employees. In the econometric estimations, we also use the variable $LnI_{no\text{-}ICT}$ which corresponds to the investment in machinery and equipments other than ICT equipments and LnI_{ICT} that is the investment in ICT. In accordance with Becchetti *et al.* (2003), we also introduce the investment in software reported by each firm. The items include software for goods and services production, administration software, marketing technologies, web sites and access to the Internet.[18] The labor input is measured by number of employees (LnL_i). Following the literature, we construct two *proxy* variables of human capital: proportion of employees with university education level and percentage of employees performing activities other than production ($LnHumanCapital_i$). The hypothesis is that new computing technologies allow a higher efficiency in task performance, but this higher efficiency is possible only if employees have appropriate skills.

In relation to organizational changes, the EDIT asked about firm investments in 17 different management technologies. Among these are: quality control, permanent improvement, total quality management (TQM), just-in-time (JIT), changes in the structure of services and production lines, project reengineering, benchmarking, vertical and horizontal disintegration and flexible manufacturing cells, among others. For estimation purposes, we use a *proxy* variable of organizational changes: a dummy that takes the value 1 if the firm implemented organizational innovations in any of the 17 management technologies and zero otherwise (*D_Management*). With respect to technological innovations and following Romo and Hill (2006), we create a categorical variable (*Innovation*) which takes the value zero if the firm did not implement any innovation at all, 1 if the firm implemented process innovation, 2 if it developed product innovation and 3 if it developed both types of innovations.[19] A justification for proceeding this way is the analysis of Kamien and Schwartz (1982), who point out that product innovations are associated to a new production function, while process innovations are related to a shifting of the actual production function.

Additionally, the econometric estimations control for several other firm characteristics (vector of variables Z_i): firm size,[20] age and dummy variables related to ownership (foreign/

[18] As a complementary measure, we use aggregate data of investment in ICT equipments in addition to the investment in ICT software (I_{ICT_SOFT}).

[19] The EDIT did not *explicitly* ask if the firm developed product, process innovation, or both. However, Chapter III, “Objectives, Results and Idea Sources for the Technological Innovation”, introduces a section asking about the “*state of progress”* with regard to the technological activity. This section asks for a total of 7 items and 44 objectives of innovation and technological development. Of these 7 items, 3 refer to the introduction of new or improved *products* for the domestic or international market and 2 refer to *new processes*. The manager had to answer each of the 7 items and 44 objectives with either: *obtained, dropped, in process and does not apply*. From the 44 objectives, we will restrict ourselves to the first 7, which are “Associated to the market and products”. We created dummy variables related to *product innovation* with the value of 1 each time the answer was “obtained” on the 3 items of the state of progress for the 7 objectives, and otherwise zero. Then we added the 21 possible results and created a dummy of product innovation for those firms that reported “obtained” in the “*state of progress*” in at least one of the objectives. In a similar way, we construct the dummy *process innovation*, but taking the answer “obtained” for the two questions on process innovation in the “*state of progress*” section.

[20] We introduced 4 different size dummies: *Small* (less than 50 employees), *Med* (51-100), *Med-Lge* (101-200), *Large* (201-500) and *Very Large* (more than 500 employees).

national),[21] exports, industrial sectors (22 dummies by ISIC Rev.3) and presence of R&D Center.[22] Finally, we include in equation (1) interaction terms between ICT investments, human capital and organizational changes in order to test for complementarities among these input factors.

Table A.1 in the Appendix displays basic statistics of the estimation variables by firm size. The data shows high heterogeneity by firm size. Additionally, Table A.2 displays the correlation matrix of the estimations variables. It shows relevant correlations between most variables and, especially, between labor productivity and ICT and non-ICT capital stocks. Additionally, it shows that the correlation between human capital and productivity is significant at 5% and no significant correlation between productivity and organizational management. Finally, age, R&D center and innovation are positively correlated to productivity.

5. Econometric results

We develop two cross-sectional econometric estimations using ordinary least squares correcting by heteroskedasticity. In the first estimation we analyze the effect of investment in ICT, human capital and organizational change on labor productivity. In the second estimation, we present evidence concerning the hypothesis of complementarity, following Giuri *et al.* (2008). Tables VI.8 and VI.9 present the estimation results. Each column corresponds to subsequent estimations that include new explanatory variables.

The most important result is the positive and highly significant impact of ICT investment on labor productivity. This is consistent across the different econometric specifications (see Table VI.8). Additionally, there is positive correlation between human capital and labor productivity (column 2). This result verifies the findings of Arvanitis (2005), Bresnahan *et al.* (2002), Black and Lynch (2001), among others. Additionally, the impact of human capital is robust to the inclusion of other covariates (see columns 3 to 6). The coefficient associated to the organizational change variable is not significant in all estimations. Thus, the hypothesis that organizational changes affect labor productivity is not verified. We may consider that these changes take time to have a relevant impact on productivity. A second aspect which may obscure the real relationship among these variables is the proxies used.[23] Finally, as can be seen in column 5 and 6, there is a positive relationship between

[21] This dummy variable is equal to 1 if more than 50% of the capital is national and zero otherwise.

[22] This dummy variable is equal to 1 if the firm has employees working in R&D activities and zero otherwise.

[23] The measures used in the literature are multiple. For instance, Arvanitis (2005) used delegation of responsibilities of managers to employees, capacity of employees to solve problems (directly) in the production area, capacity of employees to contact customers directly, reduction of number of administrative levels; and Black and Lynch (2001) used reengineering, benchmarking, number of administrative levels, proportion of employees in self-directed equipments, among others.

innovation and productivity in the presence of investment in ICT, qualified human capital and organizational changes. This relationship is robust to the inclusion of other covariates.

Other interesting implications can be inferred from the control variables in the estimations. For instance, it seems that there is no relevant relationship between the age of the firm and labor productivity. Additionally, the dummy variable of export condition is highly relevant and has a positive sign. The variable that control for the presence of R&D employees is non-statistically significant across all estimations. This may reflect that the sole presence of personnel involved in R&D activities is not enough to increase productivity. Finally, the negative coefficient of the variable *D_National* shows that national firms obtain lower productivities in relation to foreign firms.

Table VI.8

OLS estimations 1

Variable	1	2	3	4	5	6
$LnStock_{ICT}$	0.1475***	0.0998***	0.0998***	0.0929***	0.0917***	0.0855***
$LnStock_{NO\text{-}ICT}$	0.1305***	0.1262***	0.1261***	0.1225***	0.1228***	0.1168***
LnPersonnel	0.0601**	0.1032***	0.1031***	0.0527*	0.0408	0.0334
LnHuman Capital		1.5974***	1.5972***	1.5906***	1.5640***	1.4947***
D_Management			-0.0062	-0.021	-0.0189	-0.0171
D_Export				0.3476***	0.3447***	0.3283***
D_R&D				-0.0382	-0.0422	-0.0443
LnAge				0.0082	0.0107	0.0156
Innovation					0.0342***	0.0374***
D_National						-0.3355***
Small (20-50)	-0.0918	0.0081	0.0077	0.0052	-0.0106	0.0333
Medium (50-100)	0.064	0.1499	0.1498	0.1363	0.1216	0.1625
Medium-large (101-200)	0.0847	0.1476	0.1473	0.1392	0.1292	0.1574
Large (201-500)	0.2085**	0.2507**	0.2505**	0.2616***	0.2509**	0.2708***
Constant	7.5907***	7.4822***	6.5739***	7.7282***	6.5621***	8.1256***
N	5 045	5 045	5 045	4 878	4, 890	4 878
R^2adj	0.268	0.3013	0.3011	0.3288	0.3304	0.3356
F	54.2135	59.6083	60.3888	63.1316	60.002	60.6993

Source: Author's own elaboration.
*Note: *, **, *** denotes statistical relevance at 10%, 5% and 1% level; heteroskedasticity-robust standard errors. Estimations include -but not reported- dummy variables at sectoral (ISIC – Rev. 3) and geographical levels.*

Milgrom and Roberts (1990, 1995) developed theoretical models associated to the modern theory of the firm where the complementarity of ICT investment with organizational changes and personnel qualification plays a key role. Following this argument, we test a fifth hypothesis: *there exist complementarities between ICT investment, human capital* *and organizational change that affect labor productivity positively*. Following Giuri *et al.* (2008), we include interaction terms between ICT investments with the *proxy* variables of human capital and organizational change. The purpose is to analyze which type of complementarities affect labor productivity. The first four regressions include alternatively the interaction terms between ICT investment and human capital, human capital and management, ICT investment and management, and the interaction between these three productive factors (see Table VI.9). The last two columns divide the total sample in two groups: the first group which did not undertake organizational changes and the second one which did take organizational changes.

The results are mixed. Human capital and ICT investments maintain the statistical sign, magnitude and significance. The coefficient of the management variable is positive, but not relevant. Nevertheless, the interaction coefficients have all negative signs and they are almost all non-significant. This indicates that there is no complementarity between ICT investment and human capital and neither between management and human capital and between ICT investment and organizational changes. This outcome, which coincides with the findings of Giuri *et al.* (2008), could be explained by the fact that the data may not capture, in a single year, the effect of input combinations on labor productivity. It is possible to assume that, at first, organizational changes generate conflict situations that affect productivity in an even negative way. Moreover, we can expect a learning process by the employees on the use of ICT and under organizational changes. In order to make a more robust test of the complementarity between ICT and human capital, the last two columns present the regressions by dividing the sample. The results confirm the non-existence of complementarities. Indeed, for both firm groups the interaction between ICT and human capital is not significant. Again, the cross-section characteristic of the data may explain this result.

In order to analyze the robustness of the empirical results, we perform several additional estimations. First, we use sales per employee as a dependent variable. Second, we attributed ICT investment values to the firms that did not report data, following Hempell (2005). Third, a total of nearly ten different explanatory variables were used in the estimations. For instance, we estimated the model by using another proxy variable for human capital —percentage of employees performing activities other than production— and we used the Pavitt taxonomy for creating the sectoral dummy variables.[24] Basically, the main results of the estimations remain the same and it allows us to conclude that the relationship between ICT investment, human capital and organizational change, and labor productivity, is robust.[25] The implications of the positive impact of ICT investment and human capital and innovation on productivity are magnified when we observe that nearly 65% of the 5 thousand firms of the sample are small firms or have less than

[24] We use the sectoral classification proposed by Pavitt (1984) and adapted by Gutti (2008) according to several patterns of technical change: natural resource intensive; dominated by suppliers; intensive in economies of scale; specialized suppliers and dominated by science.

[25] Estimations are available upon request to the author.

50 employees. First, it is beneficial for manufacturing firms to invest in information and communication technologies, regardless of complementary investments. Second, having better trained personnel is an additional engine for obtaining gains in productivity. Finally, the innovating efforts, in whatever form, allow for productive improvements.

Nevertheless, it is necessary to clarify that some cross-section studies have reported a positive and significant relationship between ICT investments and productivity, but a non-relevant relationship and even a negative one when relying on panel data (Hempell, 2005). Indeed, cross-section studies do not capture the dynamic of entry and exit of firms and this may affect the relation investment-productivity. Finally, it is important to mention that endogeneity problems may be relevant in this type of estimations. It is necessary to expand the analysis to longer periods of time and to be able to find valid instruments that control for endogeneity. This would help in understanding the dynamic nature of the relationship between ICT, human capital and productivity.

Table VI.9

OLS estimations 2

Variables	1	2	3	4	No organiza-tional change	Organiza-tional change
$LnStock_{ICT}$	0.0922***	0.1563***	0.0916***	0.1060***	0.10028***	0.0890***
$LnStock_{NO\text{-}ICT}$	0.1228***	0.1255***	0.1227***	0.1229***	0.1229***	0.1206***
LnPersonnel	0.0411	-0.0107	0.0405	0.0403	0.0258	0.0513
LnHuman Capital	1.5894*		1.8795***	2.1136*	2.038434**	1.2375
D_Export	0.3444***	0.3662***	0.3443***	0.3442***	0.3888***	0.3077***
D_R&D	-0.0416	0.0344	-0.0443	-0.0444	-0.0278	-0.0505
LnAge	0.0106	0.0156	0.0109	0.0108	0.0429**	0.0153**
D_Innovation	0.0343***	0.0448***	0.0339***	0.0340***	0.0284*	0.0378**
D_Management		0.2213	0.059	0.222		
$LnStock_{ICT}$*LnHuman Capital	0.003			-0.037	-0.0266	0.01594
$LnStock_{ICT}$*D_Management		-0.036*		-0.025		
LnHuman Capital * D_Management			-0.549*	-0.955		
$LnStock_{ICT}$ * LnHuman Capital * D_Management				0.064		
Small (0-50)	-0.0089	-0.0948	-0.0181	-0.017	-0.0136	-0.0106
Medium-Large (50-100)	0.1225	0.0508	0.1123	0.1144	0.1524	0.0879
Medium (101-200)	0.1305	0.0734	0.1217	0.1225	0.1447	0.1091
Large (201-500)	0.2516**	0.2133**	0.2443**	0.2456**	0.2969**	0.2133*
Constant	7.7110***	7.7088***	7.6924***	7.5967***	7.5830	7.829***
N	4 878	4 878	4 878	4 878	2 149	2 729
R^2adj	0.3303	0.2989	0.3315	0.3312	0.3802	0.3076
F	62.195	56.006	61.776	58.2204	37.5200	.

Source: Author's own elaboration.
*Note: *, **, *** denotes statistical relevance at 10%, 5% and 1% level; heteroskedasticity-robust standard errors. Estimations include -but not reported- dummy variables at sectoral level, regional level.*

6. Concluding remarks

The main result of this study is that there is a positive and significant effect of ICT investments on labor productivity in Colombian manufacturing. The productivity gains are also reinforced by the investments in intangibles, such as human capital and innovation. Additionally, the exporting firms obtain a productivity prime in relation to the non-exporting firms. These results may suggest that it is necessary to support firms in order to perform this type of activities permanently.

The ICT investments, mostly through the purchase of imported hardware and software, have been encouraged by the appreciation of the Colombian peso in the last 8 years. However, the purchase of hardware and software requires financing, and although prices have also dropped in the last years due to the strong reduction of the interest rates, it is not always easily available for the small and medium firms. These two factors, appreciation of the peso and reduction of the interest rates, are important, but they can be reverted if the international financial situation changes. A more direct action to support ICT investments is to create special credit lines for the small and medium firms. A mechanism which should be consolidated is the program MiPyme Digital which the Ministry of Information and Communication Technologies launched on October 2008. This program seeks to overcome the lag of the micro, small and medium firms with regard to the ICT use, and aims at promoting the implementation of technological solutions that support their operation processes by integrating hardware, software, Internet connectivity and training. This mechanism could also be complemented by exceptions in customs duties and taxes for the purchase of hardware (imported and domestic). Nevertheless, if we want this type of investments to have a higher impact, we must also consider the importance of training the human resources.

A direct implication of the study is to spread among the managers the need to make investments on ICT goods, to improve continually the training of the employees and to develop innovative processes. Indeed, the national government and the business associations could organize regional workshops, where companies with investments in innovative processes, ICT and human capital could share their experiences so as to motivate the rest of the manufacturing firms to undertake investments in this field. In a certain way, the program MiPyme Digital seems to aim at these activities. Another implication is to implement surveys on innovation and technological development on a more regular basis in Colombia. The availability of regular data may allow researchers to determine the long-run relationship between ICT investments, organizational intangibles and innovation, and labor productivity. However, concerning the Colombian survey, it is also necessary to refine and reduce the number of questions considered in such a survey, with the purpose of obtaining more accurate answers from the managers.

Finally, it is necessary to develop more research on the subject using microdata not only in the manufacturing but also in the service sector, including financial activities. Since 2006, the EAM includes an ICT module which contains data on computers and percentage of computer use, Internet and usage activities of Internet. This new information will definitely allow for a better evaluation of the ICT impact on the performance of the Colombian manufacturing firms.

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8. Appendix

Table A.1
Variables description
(In logs)

Variables	Obs.	Mean	Std. Dev.	Min	Max	Median
Medium and large firms						
Productivity	2 072	10.29	1.03	4.18	14.33	10.27
$LnStock_{NO\text{-}ICT}$	2 049	10.57	2.37	3.71	21.98	10.26
$LnStock_{ICT}$	1 993	7.00	1.31	0.69	12.59	7.04
Non-ICT investment per employee	1 367	6.96	2.09	0	14.66	6.92
ICT investment per employee	1 008	4.93	1.62	0	14.17	4.76
LnPersonnel	2 074	4.93	0.83	3.93	8.84	4.71
LnHuman Capital	2 058	7.30	0.87	5.71	11.50	7.10
D_Management	2 074	0.56	0.50	0	1	1
D_Export	2 069	0.42	0.49	0	1	0
LnAge	2 043	2.84	0.95	0	4.57	3.04
D_R&D	2 074	0.20	0.40	0	1	0
D_Innovation	2 074	1.96	1.22	0	3	3
Small						
Productivity	3 857	9.73	0.98	2.08	17.39	9.76
$LnStock_{NO\text{-}ICT}$	3 760	9.61	1.29	2.94	15.05	9.69
$LnStock_{ICT}$	3 061	6.52	1.23	0	11.71	6.54
Non-ICT investment per employee	1 299	4.98	1.68	0	10.48	5.05
ICT investment per employee	896	3.29	1.06	0	6.65	3.16
LnPersonnel	3 903	2.86	0.67	0	3.91	2.89
LnHuman Capital	3 902	5.19	0.71	0.69	6.50	5.24
D_Management	3 903	0.31	0.46	0	1	0
D_Export	3 852	0.13	0.34	0	1	0
LnAge	3 661	2.43	0.99	0	4.63	2.71
D_R&D	3 903	0.04	0.18	0	1	0
D_Innovation	3 903	1.35	1.33	0	3	1

Source: Author´s elaboration based on EDIT 2005 and EAM 2004.

Table A.2
Spearman correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10
1. Productivity	1									
2. $LnStock_{NO\text{-}ICT}$	0.414*	1								
3. $LnStock_{ICT}$	0.407*	0.503*	1							
4. Non-ICT invest-ment per employee	0.301*	0.204*	0.237*	1						
5. ICT investment per employee	0.326*	0.374*	0.239*	-0.014	1					
6. LnPersonnel	-0.012	-0.002	-0.021	-0.006	-0.004	1				
7. LnHuman Capital	0.262*	0.153*	0.135*	0.380*	0.063*	0.005	1			
8. D_Management	0.178*	0.1998*	0.2703*	0.2389*	0.0936*	0.004	0.117*	1		
9. D_Export	0.223*	0.2051*	0.181*	0.296*	0.177*	-0.019	0.1984*	0.1185*	1	
10. LnAge	0.169*	0.1173*	0.1203*	0.273*	0.114*	-0.027*	0.132*	0.055*	0.137*	1

Source: Author´s elaboration based on EDIT 2005 and EAM 2004.

II. ICT in Chilean firms

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1. Introduction

The impact of information and communication technologies (ICT) on firm performance has been largely studied at international level, but not so much at the regional or national level. Indeed, the evidence for the case of Chile is not only scarce but also almost nonexistent, as a consequence of the few data available that could help to assess this impact. The problem is not a minor one, because a deeper analysis on the subject would help to clarify how investments in these type of goods generate positive effects not only in terms of firm's operational outcomes, but also how externalities are transmitted to other sectors, favoring cost reductions, higher market shares, the speed for adopting new technologies, and increase success probability of new products, among others.

The economic literature on this issue leads to the conclusion that in the developed world, the incorporation of ICT generates impacts at different levels in the society. This has evident innovation and competition implications, not only at firm level but also in a more aggregated form. Unfortunately, there is no consistent evidence concerning this impact in Chile. In this perspective, this study uses a small database that may help to visualize the ICT impact on the productive environment at firm level. Without being representative at all of the actual national situation, the purpose of this analysis is to encourage research lines which have not been studied much in Chile and, at the same time, to identify the importance of relying on data at firm level that allow evaluating the impact of ICT and its implications from a public policy point of view.

The study is organized as follows. Section 2 briefly discusses academic literature. Then, Section 3 describes the empirical data and Section 4 presents some preliminary analysis. Section 5 explains the theoretical model and presents econometric results. Finally, Section 6 concludes.

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2. Literature review

The impact of information and communication technologies (ICT) is an interesting issue due to the great number of potential positive externalities they generate. The ICT have been related to better productive processes within firms, better results in education, phasing out of information asymmetries in the final goods market, and to the evolution of the political process, among others. At international level, the evidence is strong for OECD member countries and especially for Europe, but not in developing countries and neither in Chile. Overall, research studies dealing with Chile have focused mainly on ICT effects over different variables that measure school performance. However, due to the lack of data, the relationship between firm economic behavior and ICT has been practically ignored.

The evidence suggests that ICT adoption would also affect macroeconomic scenario, as Lee *et al.* (2005) discuss. Using time series for 20 countries, these authors show that ICT investments contributes significantly to economic growth in many developed and newly industrialized countries, but not in developing countries. The authors use Solow residuals as dependent variable, which contains everything that capital and work are not able to explain. Therefore, it is possible to avoid endogeneity problems from other studies in which the dependent variables are country growth rates.

The ICT literature related to its impact at firm level may be categorized in two main areas. The first category of research seeks to understand how ICT are adopted in firm productive processes. The second category studies ICT impact on different firm outcomes, such as productivity, earnings and costs. With regard to the first category, Hollenstein and Woerter (2008) study the determinants of e-commerce adoption and its dissemination within the firm and among firms in Switzerland. The authors use a transmission model which incorporates rank, epidemic, stock and order effects to demonstrate that dissemination of e-commerce is due to expected benefits, adoption costs, technological opportunities, market competition, firm size and information spillovers. Bayo-Moriones and Lera-López (2007 also analyze ICT adoption. In their study, the authors use a Spanish database to evaluate the importance of five groups of variables in ICT adoption: firm environment, firm structural characteristics, human capital, competitive strategy and internal organization. The results related to environment variables are ambiguous,[2] while structural characteristics show more consistent results. Being part of a multinational group affects the adoption of ICT positively. In relation to firm size, it depends on whether you take into account the number of employees (plant size, in which the result is non-relevant) or number of plants (firm size, which is relevant and positive).With regard to human capital variables, the results are not clear: higher qualification of employees has a

2 The market competition is relevant only in a few analyzed ICT technologies. The presence in international markets displays positive results in the case of Internet and other communication technologies. Finally, there are no big differences between manufacturing and service sectors.

positive effect in ICT adoption, but greater experience/age is not relevant. Additionally, a competitive strategy is not significant for adoption, but internal organization is important, particularly using quality control equipment.

We may infer from the literature that ICT adoption success depends on the qualification of the employees. The logic behind it is that better qualified workers would achieve a more efficient ICT adoption. In other words, the learning curve would be more inclined, with more learning in less time. This means that benefits of ICT investments will be perceived more quickly by those firms with better qualified employees and with organizational structures which encourage efficient adoption of technologies. For example, Hempell (2003) uses longitudinal data for Germany —in an interrelated factor demand model— to show complementarities between ICT and human capital investments. However, Hempell (2003) emphasizes that, although ICT requires more investment in human capital, the latter cannot be achieved only with firm training, but it has to be provided by formal education. Lucchetti and Sterlacchini (2004) use a database of small and medium size enterprises in northern Italy which divide ICT in three groups: "general use", "production integrators" and "market-oriented". They show that firms with better educated employees tend to invest and use more ICT in the "market-oriented" group, which is the second ICT group with more expensive technological requirements. Further information on this point is provided by Arvanitis (2005) who studies the complementarities between ICT, innovation in organizational practices and human capital in Switzerland.

The ICT impact on different outcome variables such as productivity, costs or earnings has been analyzed for decades. This literature, however, shows a high level of endogeneity between firm characteristics, ICT adoption and its impact on outcome variables. These variables may be classified according to the aggregation level: establishment/plant, firm, industry and country. Matteucci *et al.* (2005) use aggregated data to compare ICT effects between the United States and Europe with data at country and industry levels. Their results point out that ICT impact on productivity, measured by total-factor productivity (TFP), is higher in the United States than in Europe, but there are large differences among European countries.

The canonical model in the literature is a Cobb-Douglas production function with an additional input. In other words, the production function has two types of capital: capital assets and ICT.[3] Baldwin and Sabourin (2001), following the canonical model, use a performance longitudinal database of Canadian firms and combine it with a cross-section database with information on ICT. They investigate the ICT impact on market shares and productivity. The results show that ICT investing firms are associated to productivity gains and to market share increases. On the other hand, Hempell (2005), by using a

[3] See Indjikian and Siegel (2005) for a literature review concerning ICT impact on several outcome variables and at different aggregation levels.

German panel database, finds a highly relevant impact of ICT investments. In particular, Hempell (2005) shows that a 1% increase in ICT raises firm value added in 0.06%, which corresponds to a net return rate of ICT investment close to 50%. The author attributes this high positive impact to a higher unobserved efficiency in adjustment costs, innovation efforts and training of professional staff, among others. Nevertheless, the author corrects by different biases (self-correlated residuals, different types of work, flexible functional form) and, taking these extensions into account, concludes that the aforementioned effects are overestimated in the canonical model.

Using longitudinal data also for Germany, Zwick (2003) finds a positive and relevant effect of ICT investments on productivity in manufacturing plants. However, unlike other studies, Zwick (2003) incorporates those firms which have no ICT capital in the sample and uses instrumental variables to correct for endogeneity. It should be noted that the author also measures lagged effects of ICT investments, recognizing the lag and the learning curve related to this type of investments. As a matter of fact, the results show that plants with ICT investments in 1996 or 1997 had an average productivity almost one logistic point higher than those that did not invest in ICT for the period 1997-2000. Gago and Rubalcaba (2007) study ICT effects on innovation in different outcome variables. The authors estimate several Ordered Probit models where the dependent variables correspond to innovation effects on different firm dimensions such as productivity, market expansion and service quality. This study uses an ad hoc qualitative survey made in Madrid-Spain and it uses ICT investment as explanatory variable. It is also worth mentioning that estimations control by selection bias. This methodology differs greatly from previous ones, but tells us nothing about the true impact of ICT on outcome variables: it only shows that perception of innovation effects depends on ICT use.[4]

Overall, the economic literature indicates that in the developed world, ICT investments are associated to productivity increases and that these investments are complemented by qualified employees. Also, these studies emphasize permanent endogeneity problems. The use of longitudinal structures is a common approach to solve them. In particular, using panel databases permits to evaluate dynamic effects of ICT investments on performance variables, such as sales, productivity and employment. Unfortunately, the literature also shows that there is no evidence in Chile on these matters. Indeed, it is necessary not only to face these challenges in the national context but also go further in methodological issues. In particular, methodologies associated to the literature of program impact evaluation would add important contributions to estimate the ICT impact on firm performance (Heckman and Honore, 1990).

4 The data available in this study only allows a methodology similar to Gago and Rubalcaba (2007).

3. Data

This study uses data from the BIT-Chile Survey 2007, carried out by Department of Sociology of Pontificia Universidad Católica de Chile. This survey was implemented to 301 representative firms of Región Metropolitana.[5] It should be noted, however, that the purpose of this study was not oriented towards a quantitative characterization of the ICT impact and even less to be representative of the whole country. The survey design aims at a qualitative report of the impact and penetration of these types of technologies, omitting partially quantitative questions.[6] This problem shall be considered in the empirical exercise insofar as, and as discussed later on, the lack of this type of variables not only affects in terms of omitted variable problem (generating an important estimation bias), but also the statistical relevance of many parameters. This database has a similar spirit to the one used by Gago and Rubalcaba (2007), but its quality is much lower. An important difference is the greater number of variables that describe the productive past of the firm.

Finally, a last relevant point concerning the database is its real representativity of Chilean firms. Not only the number of observations is very limited, but there are also unknown variables such as main line of business, exports status, property structure, among others, that are essential to characterize the ICT impact. This demonstrates the importance of relying on data sources specially oriented towards explaining quantitative aspects associated to ICT adoption and use in Chile. Nevertheless, and considering these weaknesses, we display some preliminary analysis and then we continue with the econometric estimations.

4. Preliminary analysis

Table VII.1 shows a set of different indicators by firm size. As can be seen, most of firms considered are small firms, and medium and large ones have a lower frequency in the records. The data also confirms the correspondence between sales and employment. What really attracts our attention is that ICT budget, as percentage over sales, is higher in micro and small firms than in medium and large firms. In a similar way, the percentage of ICT employees decreases with firm size. With regard to outsourcing, however, it is confirmed that large firms have a higher tendency to spend on outsourcing as a percentage of sales. Although the number of firms doing outsourcing is similar for all firm sizes, the allocated expenditures are much higher for large firms. Moreover, ICT outsourcing budget increases in relation to non-ICT outsourcing spending as firm size increases.

5 The results of this survey are described in Godoy *et al.* (2008).

6 A meticulous revision of the statistical information, discarding inconsistencies and missing data, leaves us a refined database with 169 observations.

On the other hand, when disaggregating by productive sector, there are significant differences in terms of ICT use and investment. Table VII.2 shows that firms in services assign four times more resources to ICT than manufacturing firms (as percentage of sales). However, this conclusion is reverted if we consider the percentage of ICT employees. This could be explained by cost and productive structure that obviously distinguishes both sectors, which is reflected by the fact that service firms are generally smaller. When analyzing the statistical information in terms of specific questions, we obtain interesting results. First, 72% of managers mention that ICT increases sales; and only 2.1% considers that introduction of this type of technology has negative effects on sales (see Table VII.3). When analyzing the question about ICT impact on profits, answers show similar patterns. Finally, answers indicating that ICT increases margins also predominate. Also, the percentage of managers who mention that margins are maintained is higher (35.3% for margins versus 25.8% for sales and 27.3% for profits) (see Table VII.3).

These results show that there is a scale effect in the perception of ICT effects on sales and profits. This effect is perhaps due to the fact that managers do not necessarily associate ICT to productive processes, but rather to the overall firm management. This is confirmed when we look at answers concerning ICT impact on production costs. Table VII.3 shows that a significant majority of managers believe that ICT has no impact on production costs (55.5%), while only 19.8% declare that ICT reduce production costs. This confirms that, from managers' perspective, ICT have an impact mainly through mechanisms that increase incomes, but not necessarily making productive processes more efficient.

Therefore, this preliminary analysis shows that the perception of ICT impact is not linked to the productive process, but rather to sales, new businesses or others. In the next section we present an econometric model to explain some of the patterns discussed.

Table VII.1
Descriptive statistics by firm size[7]

Variables	Micro	Small	Medium	Large
Obs.	12	58	53	46
Sales (millions)[a]	19.2	197.0	745.0	2 440.0
ICT Budget (millions)	1.0	7.5	28.7	414.0
Percentage ICT sales (%)	5.7	4.3	2.8	3.0
Employees (number)	36.1	48.5	64.5	317.5
ICT Employees (number)	11.9	8.8	6.0	18.6
Percentage of ICT employees (%)	33.0	18.2	9.4	5.9
PC (number)	36.1	18.1	41.0	117.7
Outsourcing ICT firms (number)	2	17	19	20
Budget outsourcing ICT (millions)	0.1	0.5	5.0	52.6
Outsourcing non-ICT firms (number)	2	17	18	19
Budget outsourcing no-ICT (millions)	19.8	16.2	8.9	65.3

Source: Authors' own elaboration based on BIT-Chile 2007; [a] Monetary values are expressed in Chilean pesos.

Table VII.2
Descriptive statistics by sector

Variables	Manufacturing	Services	Manufacturing and services	Neither
Obs.	34	84	44	7
Sales (millions)[a]	55 200.0	2 210.0	2 520.0	1 850.0
ICT Budget (millions)	371.0	65.8	53.9	66.6
Percentage ICT over sales (%)	0.7	3.0	2.1	3.6
Employees (number)	125.6	159.0	77.8	31.6
ICT Employees (number)	9.0	10.1	14.9	3.1
Percentage of ICT employees (%)	7.1	6.4	19.1	10.0
PC (number)	31.6	76.9	32.8	12.9
Outsourcing ICT firms (number)	4	12	23	19
Budget outsourcing ICT (millions)	3 036.0	458.6	249.8	228.8
Outsourcing non-ICT firms (number)	4	11	23	18
Budget outsourcing no-ICT (millions)	3 312.0	1 044.7	416.3	404.9

Source: Authors' own elaboration based on BIT-Chile 2007; [a] Monetary values are expressed in Chilean pesos.

[7] The firm size is determined by the Chamber of Commerce of Santiago (Camara de Comercio de Santiago) based on sales and employment records of the firm.

Table VII.3[8]
Response distribution of ICT impact answers over different outcome variables
(Percentages)

Response	Sales	Profits	Margins	Production costs
Reduces	2.1	2.0	2.4	19.8
Maintains	25.8	27.2	35.3	55.5
Increases	72.1	70.8	62.3	24.7
Total	100.0	100.0	100.0	100.0

Source: Authors' own elaboration based on BIT-Chile 2007.

5. Empirical model and results

This section estimates different quantitative models to analyze which firm characteristics are related to the individual perception of ICT impact on a set of firm performance indicators. One of the database characteristics is that most of performance indicators have an ordinal nature. This fact conditions both structure and estimation methods and public policy implications. In effect, the database information relies on a report on how different managers qualify technology impact in different types of economic and operational results. The questions include subjects regarding impact on costs (operation, production, advertising, promotion and customer service, among others) and market introduction time of new products, number of new products, market share and incomes, among others. All things considered, we observe what individuals infer with respect to ICT effect on those variables.

The answers are qualitative and ordered according to the impact considered. For example, when evaluating the impact of technology investment on personnel cost, the managers answer among options such as: "it reduced significantly", "it reduced", "it remained stable", "it increased" or "it increased significantly". This type of answer presents an important methodological challenge in order to evaluate the variables that may determine better (or worse) results, for each category, of this type of investment at firm level. In this perspective, the most common approach is to use models with ordered answers, which come from models with binary dependent variables. One of these models is the "*Ordered Probit Model*", where potential results are not cardinal, but only ordinal. In other words, we have different types of answers which are mutually excluding and that are only related in terms of order.

8 Self-elaboration based on the refined base BIT-CEPAL.

The basic structure an Ordered Probit model is as follows:

$$y_i^* = \beta' x_i + u_i$$

Where x_i is a vector of observable characteristics of firm i and u_i is the error term. Nevertheless, y_i^* cannot be observed directly because it is assumed to be a continuous variable. Therefore, it is necessary to define a new variable —denoted by y_i — which explains the discreet structure associated to managers' answers, as previously discussed. A way of doing this, and due to the ordinal structure of answers, is through the following relationship:

$$y_i \begin{cases} 0 \ \ if \ \ y_i^* < d_0 \\ 1 \ \ if \ d_0 \leq y_i^* < d_1 \\ . \\ . \\ . \\ J \ \ if \ \ d_{J-1} < y_i^* \end{cases}$$

Where, each value of d_i represents a threshold which orders different types of answers, showing an ordinal-natured ordering only. Empirically, these thresholds are already determined by the answers themselves. According to this specification, it is possible to estimate the probability of observing each scenario based on the following structure:

$$\Pr(y_i = 0) = \Pr(y_i^* < d_0) = \Pr(\beta' x_i + u_i < d_0) = \Pr(u_i < d_0 - \beta' x_i)$$
$$\Pr(y_i = 0) = F(a_0 - \beta' x_i)$$

$$\begin{aligned} \Pr(y_i = j) = \Pr(d_{j-1} \leq y_i^* < d_j) &= \Pr(d_{j-1} \leq \beta' x_i + u_i < d_j) \\ &= \Pr(u_i < d_j - \beta' x_i) - \Pr(u_i < d_{j-1} - \beta' x_i) \\ &= F(d_j - \beta' x_i) - F(d_{j-1} - \beta' x_i) \end{aligned}$$

Where $F(\cdot)$ corresponds to a type of probability distribution function to be defined which characterizes the error term, usually modeled by logistic and normal distributions. The model is estimated for a set of outcome variables. In particular, for ICT impact on sales, profits, margins and production costs. Once more, it is important to highlight that what is estimated is the covariance of ICT impact perceptions on outcome variables, controlling by firm characteristics. This is in no way an estimation of quantitative ICT effects on firm performance variables.

Therefore, using an Ordered Probit model, we describe managers' answers according to several control and "ICT effort" variables. The "ICT effort" variables are basically two: percentage of ICT employees and ICT budget as percentage of sales. Each type of effort includes a scale variable and a proportional scale variable. Table VII.4 shows descriptive statistics of estimation variables. The control variables correspond to firm economic sector classification (dummy variable for each sector category). However, these dummy variables are indicative, but not excluding. This means that a firm may report to belong both to manufacturing and service sectors.

Table VII.4
Descriptive statistics of estimation variables

Variable	Obs.	Mean	Std.Dev.	Min	Max
Total employees	169	125.9	477.2	2.0	6 000.0
ICT employees (%)	169	18.8%	0.3	0.0%	100.0%
Log (sales)	169	20.3	2.0	13.2	28.2
Log (ICT budget)	169	16.5	1.9	11.2	23.1
ICT budget (%)	169	3.6%	0.0	0.0%	33.3%
Production	169	46.2%	0.5	0.0%	100.0%
Services	169	75.7%	0.4	0.0%	100.0%

Source: Authors' own elaboration based on BIT-Chile 2007.

Thus, in the framework of an Ordered Probit model, we estimate the following equation:

$$y^* = \beta_1 TotalEmployees_i + \beta_2 ICTEmployees_i + \beta_3 LogSales_i + \beta_4 LogICTBudget_i + \beta_5 ICTBudget_i + \beta_6 Manufacturing_i + \beta_7 Services_i + \varepsilon_i$$

The estimation results in Table VII.5 show that, in most cases, neither control nor ICT effort variables are relevant for the perception concerning ICT impacts. Nevertheless, there are also some significant coefficients. With regard to production costs, we find that the probability that an individual attributes a production cost increase because of ICT, increases with number of employees and with percentage of ICT employees and percentage ICT budget over sales, and it decreases with absolute ICT budget and if the firm belongs to service sector.

These results show that larger firms tend to attribute production cost increases to ICT. Likewise, more ICT employees are associated to attributing production cost increases to ICT. On the other hand, firms with higher ICT budget tend to associate production cost reductions with ICT, which could be associated to managers' conviction regarding ICT benefits in making processes more efficient. However, when measured as a percentage of sales, ICT budget is associated with production cost increases. Finally, service sector ascribes production cost reductions to ICT incorporation. These results show that managers in the firm end up associating accounting cost with production costs, rather than processes' improvements. That is, ICT employment is seen more as an expense than a complementary effort to ICT investments aiming at improving efficiency. The same applies to ICT budget as a percentage of total sales. ICT are associated to improvement of productive processes only when it is measured at budget level.

In addition, there are no statistically relevant variables in sales, profits and margins estimations. This is partly due to the small variance in dependent variables. In fact, ICT effect on production costs is the dependent variable with highest variance and, therefore, explanatory variables are more relevant in explaining different answer categories. However, as we stated before, the case of costs is also different from the other outcome variables. Indeed, this indicates that ICT effects are related to costs in a very direct way. By contrast, ICT effects on sales, profits and margins are much more noise and difficult to perceive by managers.

Table VII.5

Estimation results: ordered probit model

Variables	Production costs	Sales	Profits	Margins
Total employees	0.0004878	0.0004011	0.0003952	0.0015462
	(2.92)**	(-0.75)	(-0.96)	(-1.91)
ICT employees (%)	1.0376117	0.4071807	0.291435	0.4656008
	(2.78)**	(-1.12)	(-0.84)	(-1.38)
Log (sales)	0.136591	0.0318005	0.0452136	-0.0334052
	(-1.34)	(-0.34)	(-0.48)	(-0.39)
Log (ICT budget)	-0.2079326	0.041063	-0.0229262	0.0523931
	(2.30)*	(-0.42)	(-0.24)	(-0.6)
ICT budget (%)	8.2761751	0.4262619	0.3356526	-1.6565388
	(2.62)**	(-0.15)	(-0.12)	(-0.54)
Manufacturing	0.0388378	0.2623126	0.1424386	0.2982099
	(-0.19)	(-1.16)	(-0.64)	(-1.35)
Services	-0.5383545	0.3692817	0.2041689	0.2514351
	(2.22)*	(-1.56)	(-0.85)	(-1.02)
Obs.	169	169	169	169

Source: Author's own elaboration.
*Note: z-statistics in absolute value with robust standard errors in parenthesis; * Significant at 5%; ** Significant at 1%.*

6. Concluding remarks

This study presents a first effort to determine the impact of information and communication technologies on a group of Chilean firms. Unfortunately, there is not much early evidence on these effects and therefore this type of empirical exercises is noteworthy. Indeed, the empirical analysis shows the relevance of relying on microdata at firm level, also as a relevant tool in order to design appropriate public policies. Indeed, economic policies aiming at fostering ICT incorporation in large firms are not the same than for small firms, and they do not have the same effect in a firm in the shoe sector than in a firm in the electronic sector.

Nevertheless, the number of firms considered in this study is rather reduced, which generates econometric estimations with few significant relationships. It should be highlighted that this survey measures impact perceptions and not the quantitative ICT effect. From the qualitative and quantitative analysis, it may be observed that many firms ascribe certain ICT benefits in the productive systems. Particularly, firms with higher ICT budget tend to associate production cost reductions to these technologies, although ICT employment is considered more an expense than an ICT effort to improve efficiency. Unfortunately, restrictions on the firm sample and on the quantitative variables constitute a serious limitation in the correct assessment of ICT impacts on Chilean firms.

Finally, it should be mentioned that this is an exploratory research and therefore it is impossible to generalize its results. As an extension, we suggest to interview a greater number of firms, and to consider the urgent need for the survey form design to collect firm quantitative data such as sales, employment, investments, innovating behavior and exports. This would facilitate the analysis of the relationship between ICT and firm performance. From the econometric exercise, we may also conclude that, if the purpose is to find ICT effects on outcome variables, the use of qualitative surveys is not the best option, but it offers valuable data when it comes to characterizing how firms perceive or rationalize ICT. A study that seeks to determine ICT effects on outcome variables should estimate production functions or apply methodologies related to program evaluation analysis.

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III. Science and technology, ICT and profitability in the manufacturing sector in Peru

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1. Introduction

The development of the technological innovation system, innovation processes and Information and Communication Technologies (ICT) in Peru is insufficient and weak, and it also has low political priority (CONCYTEC-SINACYT, 2009; CONCYTEC, 2005; Kuramoto, 2007 and 2004; Sagasti and Kuramoto, 2003).[2] Indeed, the National Program of Science, Technology and Technological Innovation point out that there are important lags in generation and incorporation of technology in productive and social areas (CONCYTEC-SINACYT, 2009).[3] Relevant factors explaining these lags in science, technology and innovation (SCTeI) activities are: i) weak institutional framework and management of SCTeI activities; ii) low economic and cooperation resources; iii) inadequate generation of human resources and infrastructure; and iv) insufficient exploitation of information benefits.

The CONCYTEC-SINACYT report 2009 also states that Peru does not have yet a national long term development program which establishes sustainable socioeconomic development priorities. In the field of SCTeI activities, although the Strategic National Program of Science, Technology and Technological Innovation for Competitiveness

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[2] The Technological Innovation System is defined as a dynamic network of agents interacting in an economic area under a specific institutional infrastructure and involved in generation, diffusion and use of technology (Carlsson and Stankiewicz, 1991). In broad terms, innovation process is defined as the change in the thinking process in order to make something useful. These changes may be in products, processes or administrative aspects (McKeown, 2008). Schumpeter (1934) distinguishes invention, as ideas that manifest themselves, from innovation, which are ideas successfully applied in practice.

[3] According to the Global Competitiveness Report 2009 (WEF, 2009), Peru held position 85 of 133 countries in the technological innovation index; the United States was top one, Chile leaded in Latin America and the Caribbean with position 43, and Paraguay was the country with less technological performance in the region with position 131. On the other hand, in the ICT use indicator, Peru held position 77, Switzerland was top one, Barbados held position 41, the best among Latin American countries, and Bolivia held the lowest position, 128 out of 133 countries.

and Human Development 2006-2021 is in effect, no integral programs of national and regional scope in productive, social and environmental areas have been generated. The reason is that authorities and both national and regional leaders do not give high priority to scientific knowledge and technology, as one of the most important means to achieve sustainable economic growth, poverty reduction and improvement of the quality of life of Peruvian people. Additionally, organizations having technologies and qualified human resources that are able to support large infrastructure and development projects that are being executed and planned in different productive sectors, are inadequate. Moreover, not only central government but also regional and local governments have not formulated sustainable programs to integrate poor populations into the productive systems, and the link between universities and research institutes with firms is weak.

Kuramoto (2007a and 2007b) states that science, technology and innovation have not been dealt much in the country. Clear evidence is the scarce literature on the subject and the disappointing innovation and technological indicators in Peru. Indeed, R&D spending share in relation to GDP is less than 0.11%; productive structure specializes in primary activities and services of low value added; and primary exports dynamism do not create employment. In fact, these are highly capital intensive sectors with basic technological requirements, such as mining, petroleum and fishing. On the other hand, lack of interrelations between different agents in the innovation system does not allow knowledge transmission throughout the whole economy. Also, the government does not give priority to technology nor does it provide important financing resources. Along the same line, firms do not understand the relevance of innovation and there are not enough human resources involved in the innovation processes. Moreover, Sagasti and Kuramoto (2003) establish that *"at the beginning of the 21st Century there is no Technological Innovation System in Peru and that it only relies on some components, rather weak and scarcely linked among each other, in certain fields of the scientific, technological and productive activity"* (p.10).[4]

Additionally, the analysis of the National Survey of Science, Technology and Innovation 2004 (Encuesta Nacional de Ciencia, Tecnología e Innovación) by CONCYTEC (2005) reports the following facts. First, the proportion of firms that perform SCTeI activities is low, and the activities are concentrated in metropolitan Lima. The mega and large firms are the firms with more initiatives in this field. These activities are developed in different sectors, emphasizing food, beverage and tobacco, mining, commerce and petroleum.

[4] The national innovation system in Peru is also characterized by the following characteristics: i) universities, public institutions and firms have few high-level research centers available, and probably a high proportion of these centers does not comply with international standards regarding research quality, results and publications; ii) there is a limited number of firms implementing innovations on a permanent and systematic basis; iii) institutions which formulate science and technology policies are weak and do not rely on financial and human resources nor on political influence that are necessary to promote the creation of a National Innovation System, or at least Sectoral Innovation Systems; iv) physical infrastructure, which constitutes the basic support for innovation, show several limitations, and v) very few institutions help to create a favorable environment for science, technology and innovation.

Second, availability of R&D formal units decreases as firm size decreases. Third, the main application of R&D spending activities is experimental research, then applied research and, lastly, basic research. Also, firm R&D investment is mainly financed by own resources. Fourth, most firms have computers and access to the Internet, although the proportion is less for small and medium size enterprises. The access to ICT is significant, but it varies depending on technology sophistication level and firm size. Fifth, part of innovation activities is oriented towards product innovation and organization. Moreover, innovations have shown a higher novelty grade in the framework of the firm itself and/or local market. Sixth, Peru innovation capacity faces big challenges ahead. In general, lack of access to financing and high cost of training are two main obstacles for innovation activities across all firm categories.

In this perspective, this study has two main purposes: i) to report indicators of science, technology and technological innovation, cooperation and ICT in Peru; and ii) to provide evidence on the effect of SCTeI activities and ICT on profitability in Peruvian manufacturing firms. This study is organized as follows. Section 2 shows some indicators of technological innovations and ICT use. Then, Section 3 displays evidence related to economic performance of manufacturing firms. Section 4 presents the conceptual framework and empirical approach, and Section 5 discusses econometric results. Finally, Section 6 concludes.

2. Indicators of technological innovations and ICT

Table VIII.1 shows the relative position of Peru in relation to other Latin American countries and the United States (US) regarding technological innovation (TI) indicators and ICT.[5] First, data shows that Peru and Bolivia are the countries with the lowest TI and ICT indicators in the sample. Second, except for the United States, ICT rates for Latin American countries are, in general, higher than technological innovation rates. In developed countries, like the United States, the preponderance of ICT instruments and innovation activities are similar. Third, there are significant differences in the levels of TI and ICT indicators among Latin America countries and the United States. For example, while the United States invests 2.7 cents per dollar in R&D, Peru invests 0.1 cent per dollar. Furthermore, US firms have an indicator of 77% in R&D spending, Peru has 28% and Brazil, the country with the highest rate among the region, has an indicator of 47%. There are similar differences for others ICT and TI indicators.

[5] The indexes are measured in a scale from 0 to 100. Most of the indicators in Table VII.1 come from firm level surveys in the different countries. The answers in the surveys are turned into scores in a scale from 1 to 7. The scores, S, of this scale are transformed into the scale 0-100 using the following formula: ((S-1)/6)*100. The questions and methodologies used for indexes estimations are not necessarily equal for each year and comparisons over time should be considered with caution.

Table VIII.1
Technological innovation and ICT indicators, 1998-2009

Countries	Year	Innovation index[a]	R&D/GDP[b]	R&D intensity, private[b]	Quality of scientific institutions[b]	Cooperation index[b]	Index of technological sophistication[b]	Index of technological capability[a]	Technological absorption (firms)[b]	Telephone lines (x100 inhabs.)	Mobiles (x100 inhabs.)	PC (x 100 inhabs.)	Internet users (x 100 inhabs.)
Peru	1998	n.d	0.1	21.2	24.7	30.7	26.2	n.d	34.5	6.2	3.0	3.0	1.2
	2000	27.0	0.1	23.3	25.0	33.3	28.3	45.2	63.3	6.6	4.9	4.0	3.1
	2004	19.7	0.2	26.7	30.0	21.7	38.3	40.8	46.7	7.5	14.9	8.4	11.7
	2009	28.5	0.1	28.3	31.7	33.3	39.8	39.8	58.3	10.0	72.7	10.1	24.7
Chile	1998	n.d	0.5	31.8	39.3	45.0	53.5	n.d	60.7	20.3	6.4	6.2	1.7
	2000	40.2	0.5	28.3	45.0	36.7	55.0	57.5	68.3	21.4	22.1	9.2	16.5
	2004	29.5	0.7	36.7	45.0	36.7	66.7	59.2	68.3	20.6	57.4	13.3	19.4
	2009	40.2	0.7	36.7	48.3	48.3	54.7	54.7	75.0	21.0	88.3	26.0	32.6
Brazil	1998	n.a	0.7	23.3	34.3	41.3	35.3	n.a	57.7	11.8	4.4	3.0	1.5
	2000	27.7	0.9	31.7	40.0	48.3	40.0	55.5	73.3	17.8	13.3	4.9	2.9
	2004	20.7	0.8	45.0	55.0	46.7	55.0	54.0	68.3	21.5	35.7	13.1	19.1
	2009	42.0	1.0	46.7	53.3	51.7	51.0	51.0	73.3	21.4	78.5	29.2	35.5
Mexico	1998	n.a	0.4	26.5	26.0	37.8	28.0	n.a	57.7	10.4	3.5	3.7	1.3
	2000	26.8	0.4	25.0	38.3	41.7	40.0	61.7	58.3	12.6	14.4	5.8	5.2
	2004	20.0	0.5	33.3	45.0	35.0	50.0	52.2	53.3	17.7	37.7	11.0	17.0
	2009	33.2	0.5	31.7	45.0	41.7	42.2	42.2	60.0	19.3	70.8	14.4	21.9
Argentina	1998	n.a	0.4	25.0	41.8	31.7	34.3	n.a	56.0	19.7	7.4	5.3	0.8
	2000	43.5	0.4	26.7	38.3	40.0	35.0	55.5	58.3	21.4	17.6	6.9	7.1
	2004	30.8	0.4	30.0	38.3	23.3	48.3	47.8	50.0	22.8	35.2	8.3	16.0
	2009	32.5	0.5	31.7	46.7	41.7	42.3	42.3	58.3	24.2	116.6	9.0	28.1
Bolivia	1998	n.a	0.3	15.8	21.8	23.2	14.0	n.a	47.0	5.7	3.0	0.8	0.6
	2000	25.0	0.3	16.7	11.7	40.0	11.7	42.0	33.3	6.1	7.0	1.7	1.4
	2004	21.5	0.3	20.0	25.0	20.0	21.7	30.2	31.7	6.9	20.0	2.3	4.4
	2009	20.5	n.a	20.0	25.0	25.0	22.3	22.3	38.3	7.1	49.9	2.4	10.5
Costa Rica	1998	n.a	0.3	40.8	58.3	46.3	51.0	n.a	65.7	19.8	2.9	8.0	2.7
	2000	41.8	0.4	31.7	56.7	41.7	51.7	66.2	70.0	22.9	5.4	15.3	5.8
	2004	19.3	0.4	43.3	53.3	35.0	55.0	49.5	61.7	31.6	21.7	21.9	20.8
	2009	44.7	0.4	46.7	60.0	55.0	45.3	45.3	68.3	31.8	41.7	31.2	33.6
United States	1998	n.a	2.6	75.3	86.5	76.3	92.5	n.a	35.2	65.2	25.1	45.0	30.7
	2000	91.7	2.7	75.0	95.0	56.7	95.0	90.3	91.7	68.2	38.8	57.1	43.9
	2004	90.2	2.6	80.0	88.3	73.3	91.7	87.3	88.3	60.7	63.1	76.4	66.3
	2009	79.5	2.7	76.7	86.7	81.7	76.8	76.8	86.7	52.6	89.0	80.6	72.4

Source: author's own elaboration based on WEF (1998 – 2009) and UNESCO (2009).
[a] Data reported for 2000 correspond to 2001;
[b] For Bolivia and Costa Rica, data for 1998 corresponds to 1999.

Tables A.1, A.2 and A.3 in the Appendix show several ICT indicators of Peruvian firms for 2004 and 2007 and technological innovation indicators for 2004. The indicators are derived from the Survey on Information and Communication Technologies of the National Institute of Statistics and Informatics (INEI, 2007) and the National Survey of Science, Technology and Technological Innovation (CONCYTEC-INEI, 2004).[6] The ICT indicators regarding the surveys 2004 and 2007 are reported in Table A.1 and TI indicators of the survey 2004 in Table A.2. The productive sectors were aggregated in the following sectors: primary, manufacturing (including construction), technological and services (private and public including commerce). Additionally, manufacturing industry was in: i) Minerals processing, ii) Traditional manufacturing (textile, clothing, etc), iii) Technological (chemicals, electric machinery, pharmaceuticals and construction of non-electric machinery); and iv) Food (including tobacco). The statistical information indicates that:

- There is a relatively extended use of basic ICT tools (computers and Internet use) in most firms and in all productive sectors.
- In 2004, primary sector obtained the lowest levels in mainly all ICT indicators. By contrast, manufacturing, and services sectors obtained the highest levels in most ICT indicators.
- Most firms did not rely on research centers for SCTeI activities.
- Most firms in 2004 and 2007 used the Internet for obtaining information on products and processes, and less than half of firms used it for customer services.
- In 2004, only 4.5% of firms developed activities related to science and technology. The proportion of mega and large firms implementing these activities was much higher than the proportion of medium and small firms. Also, manufacturing firms developed science and technology activities in a higher proportion, particularly mega and medium firms. The technological, service and commerce sectors obtained S-ACT percentages lower than 2.6%.
- Around 80% of firm employees had secondary, technical and primary education levels. Only 1.4% of firm employees had post-graduate education. Firms in technological sectors had a higher proportion of employees with higher and post-graduate education. By contrast, firms in primary sector had the lowest proportion of employees with higher and post-graduate education.
    - In 2004, the number of firms which developed innovation activities was higher

[6] The basic characteristics of the surveys are: (i) original sample size include 7,290 firms, while final sample in statistical tables comprises 4,861 firms; (ii) original sample size of the survey 2007 includes 1,393 firms and final sample comprises 1,277 firms; (iii) in the survey 2004, 61% of firms were located in the region and province of Lima and in the survey 2007, 83% were located in the same region and province; (iv) in the surveys 2004 and 2007, mega-firms (with more than 500 workers) represented 3% of total number of firms, large firms with more than 100 and up to 500 workers) represented 9% in the survey 2004 and 17% in the survey 2007, medium firms (between 21 and 100 workers) represented 23% in the survey 2004 and 20% in the survey 2007, and small firms (less than 20 workers) represented 64% of firms in the survey 2004 and 40% in the survey 2007; (v) firm sample in Table A.3 corresponding to manufacturing firms includes 1,312 firms: 49 are mega firms, 158 are large, 352 are medium and 753are small firms.

than the number of firms that developed science and technology activities in all sectors.[7] Most firms that innovated in process, product, marketing and organization areas were financed, almost completely, with own resources and invested, on average, 0.7 cents per dollar of sales. On the other side, the percentage of mega and large firms that innovated was higher than that of medium and small firms.

- Consistently, only 5.2% of firms collaborated with other institutions, and 2.9% of firms collaborated with universities or research centers. In most cases, mega and large firms coordinated innovation activities with other institutions more intensively than small firms.

These results suggest that Peruvian firms are more inclined towards ICT use rather than implementing activities in science and technology. This indicates an important bias towards using, imitating or adapting pre-established technologies by using ICT rather than generating new technologies and products through SCTeI activities and innovation investments. Furthermore, although the evidence shows that the proportion of mega and large firms implementing SCTeI activities is higher than the proportion of small firms, the highest percentage of innovation investments over total sales is for small firms (see Table A.2).

Table A.3 describes the same set of indicators disaggregated by manufacturing sectors. The technological sector obtained the highest percentage of firms implementing science and technology activities, and traditional manufacturing obtained the lowest percentage. The proportion of firms that reported cooperation or collaboration activities in innovation activities with other institutions was lower than those reporting SCTeI activities in the 4 manufacturing sectors. However, the percentage of firms performing coordination activities was much higher in mega and large firms than in medium and small firms. In coordination activities, the technological sector obtained the lowest percentage. As with the sample covering all productive sectors, mega and large firms developed science, technology and technological innovation activities more intensively. In contraposition to whole sample, mega and large manufacturing firms invested in innovation higher percentages of sales than medium and small firms. The same pattern can be observed for the percentage of spending related to

[7] In section II of the survey, science and technology activities is defined as systematic activities, closely related to the generation, production, diffusion and application of scientific and technical knowledge in all science and technology fields. In Section VI, innovation activities is defined as the actions taken by the firm aiming to apply concepts, ideas and methods necessary for acquiring, assimilating and incorporating new knowledge. The product of these actions results in a technical change, without being necessarily a technological innovation in the strict sense of the word, which has to be reflected in firm performance. Innovation implies the creation, development, use and diffusion of a new product, process or service and their relevant technological changes. It also implies changes in the organization and administration: organizational methods, process reengineering, strategic planning, quality control, etc. (CONCYTEC-INEI, 2004). In spite of these differences, the R&D spending was registered in Section II and the use of these activities was registered in Section VI. These registers meant that the firm which used the outcome of R&D activities for making process, process or organization improvements were firms that also spend on R&D and, therefore, they were counted as firms performing science and technology activities. It should be noted that, additionally to the R&D activities aiming at process, products or organization improvements, innovation includes activities in: (i) capital assets, (ii) hardware and software; (iii) technology hiring; (iv) engineering and industrial design, (v) management, and (vi) training and consulting.

SCTeI activities. On the other hand, the technological sector showed a higher percentage of employees with higher and post-graduate education and traditional manufacturing sector had the lowest percentage. Similar to the firm sample covering all sectors, the number of manufacturing firms developing innovation activities was higher than the number of firms implementing SCTeI activities. In addition, manufacturing firms performed products and process innovations more intensively than marketing and organizational innovations. Finally, almost all firms implemented innovation investments with their own resources.

Overall, Table A.3 indicates that: i) firms in traditional industries performed science and technology activities less intensively than firms in other sectors, ii) manufacturing firms performed product or process innovations more intensively than organizational and marketing innovations, iii) innovation activities increases with firm size, and iv) manufacturing firms have low level of cooperation with other institutions; and mega and large firms were more intensively involved in these.

3. Science and technology, ICT and economic performance

The evidence described in the previous section reflects a weak and deficient development in science, technology and innovation activities in Peruvian firms. This section presents indicators of economic performance for a sample of 339 manufacturing firms that answered the Annual Manufacturing Survey (INEI, 2005)[8] and the National Survey of Science, Technology and Technological Innovation of 2004. These surveys allow identifying differences in these indicators by type of activity in science, technology and innovation, by technological collaboration degree and by ICT use.

Table A.5 shows indicators related to economic performance, employment, and tangible, commercial and R&D investment resources. The indicators are classified by: i) use or not use of ICT instruments, ii) developing or not developing innovation activities, iii) implementing or not implementing science and technology activities, and iv) coordination (collaboration) that firms have or have not made with other institutions. Table A.5 indicates that firms who developed SCTeI activities have on average a higher level in: i) size; ii) sales; iii) value added; iv) rate of return; v) proportion of gross production value and value added over total capital value; vi) proportion of wages over total expenses[9] and vii) asset value per worker, than corresponding levels for firms that did not perform these activities.[10]

8 The Annual Manufacturing Survey of 2005 included 1,078 firms whose value added represents 21% of total manufacturing value added. The value added of the 339 selected firms represents 62.5% of the value added in the survey and 13.1% of total manufacturing value added in Peru.

9 Due to the fact that there is no data available on human capital, the W/A indicator is used as a proxy.

10 Due to the definition of large firm used, most firms analyzed in Table A.5 are large. In general, the Manufacturing Survey 2005 is biased towards medium, large and mega-firms.

Nevertheless, other indicators do not necessarily demonstrate the same result. For example, indebtedness indicator (PAS/PAT) and size of tangible resources (A/V and AF/AT)[11] are higher for firms that implemented no innovation activities and did not collaborate with other institutions. In the indicator of commercial resources or export capacity (X/V), firms that had a higher level in this indicator were not involved in SCTeI activities. However, the indicator X/V for firms that did collaborate with other institutions was higher than that of firms who did not collaborate. Finally, the R&D indicator was higher for firms that did not coordinate with other institutions.[12] It should be noted that the size of non-collaborating firms is smaller than the size of those firms that coordinated with other entities.

Additionally, indicators of profitability, employment, tangible resources and commercial intangibles, and investment in R&D are generally higher for firms that used ICT than for those that did not use ICT. Nevertheless, there are exceptions of indicators in which the level difference was in favor of firms that did not use ICT. For example, firms that did not use the Internet for customer service showed a higher level of export capacity indicator. Likewise, the indebtedness indicator (PAS/PAT) for firms that did not have Internet service, did not use the Internet service for customer services or did not have computers, was higher than for those firms that did use these services. Overall, this evidence indicates potential associations between SCTeI activities, ICT and economic performance in manufacturing firms in Peru. The following section estimates the statistical relevance of these associations.

4. Model and empirical approach

This section describes a basic framework which relates science, technology, innovation, technological collaboration and ICT to firm profitability. The model is based on the theory of resources and capabilities[13] and on Surroca and Santamaría (2007). In its simple form, this theory claims that firm resources and capabilities qualifies firms for obtaining greater profits than their competitors, if they have attributes such as shortage, exclusivity, durability, inimitability and non-substitutability. Mowery *et al.* (1998), Galende and Suárez (1999), Galende and de la Fuente (2003), and Miotti and Sachwald (2003) complement this theory arguing that an efficient management of resources and capabilities will provide intangible assets to firms that will guide innovation process successfully. Thus, we may distinguish between firm outcomes and innovation outcomes.

[11] See definitions in Table VIII.2.

[12] Atallaha (2002) discusses the literature of strategic investments which states that cooperation among competitors reduces R&D spending when horizontal externalities are low and it increases it when these are high. The lower R&D indicator for firms that cooperate may be consistent with this argument.

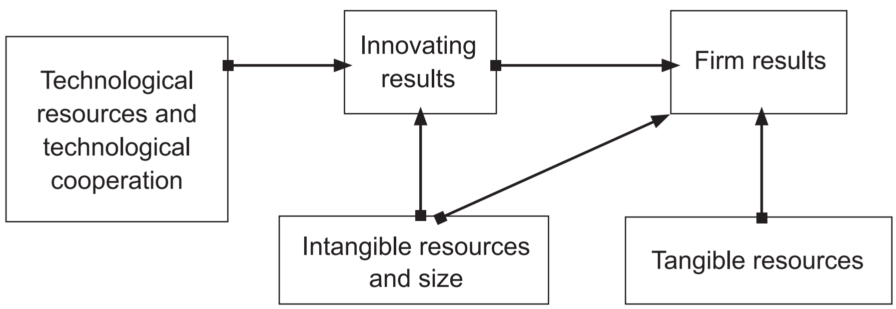
[13] For example, Dierickx and Cool (1989), Barney (1991), Amit and Schoemaker (1993), Teece *et al.* (1997) and Barney *et al.* (2001).

Surroca and Santamaría (2007) focus on the impact of technological cooperation activities on firm results (such as profitability) and innovation results (such as processes, products and organization innovations). They propose three hypotheses. First, innovations have a positive effect on firm outcomes. Griliches (1979, 1998) summarizes part of the literature which supports this idea. Crépon *et al.* (1998) complement the hypothesis arguing that innovation is a process that starts with R&D activity, it continues with patent generation and, finally, with sales of new products. Therefore, innovating outcomes mediate the relationship between R&D investments and firm results. According to these authors, R&D investment is not the ultimate determinant of firm outcome, but rather the innovation in different aspects of the firm.

The second hypothesis is that technological cooperation has a positive effect on innovation results. Galende and de la Fuente (2003) and Miotti and Sachwald (2003) argue that sometimes firm internal resources will not be enough to develop innovations. In other words, firms may lack necessary resources and capabilities to develop technological activities. In this perspective, it is necessary to have access to resources and capabilities which are external to the firm. As a result, cooperation, collaboration or technological coordination may become relevant tools. For example, collaboration agreements may solve problems of market contracting and at the same time they can allow the firms to have access to other lacking resources or resources that are complementary to their own (Kogut, 1998; Das and Teng, 2000; Hagedoorn *et al*. 2000, Belderbos *et al*. 2004b). Therefore, the complementarity between internal and external resources provided by technological partners is what triggers success of cooperation agreements and development of product, processes, marketing or organization innovations (Miotti and Sachwald, 2003; and Belderbos *et al.* (2004a).

The third hypothesis is that innovation results mediate the relationship between technological cooperation and firm outcomes. The literature dealing with the relationship between technological cooperation and firm results is scarce and the few empiric studies that estimate this relationship have ambiguous results (*e.g.* Belderbos *et al*., 2004b; Faems *et al.* 2004; Lööf and Heshmati, 2002 and Cincera *et al*, 2003). Surroca and Santamaría (2007) shows that technological cooperation has positive effects on firm innovation outcomes. Consequently, as long as firms develop innovations in products, processes or others, they shall be able to differentiate themselves from their competitors and use their productive resources more efficiently. As a result, they shall obtain greater profits. This means that the relationship between technological cooperation and firm results is not direct, but it is rather an indirect relationship mediated by innovations.

Although it is difficult to distinguish direct and mediating impacts of SCTeI activities, technological coordination and ICT use on firm economic performance, what firms expect is that these technological resources generate innovating results which lead to higher profitability. Consequently, the hypothesis formulated is that the technological resources, including technological coordination, generate innovating outcomes which may have a positive impact on firm profitability. According to the theory of resources and capabilities, in addition to technological resources, tangible and intangible resources also influence firm economic performance. As control variables, and following Surroca and Santamaría (2007), firm size and indebtedness variable are also included as profitability determinants. The expressed relationships are illustrated as follows:



The following specifications aim at verifying the empirical validity of these relationships:

$$IR_{it}= \sum\alpha_j RTec_{ijt-1} + \sum \beta_j Rin_{ijt} + \sum \gamma j\ RTan_{ijt} + \sum\theta_{jt} X_{it} + \Sigma\delta_j D_{ijt} + \varepsilon_{it} \qquad (1)$$

$$Prob\ (DINN_{jt-1}=1/Z_{it-1}\ \varphi)= 1-F(-Z_{it-1}i.\varphi) \qquad (2a)$$

$$Prob\ (DINN_{jt-1}=0/Z_{it-1}\ \varphi\ )= F(Z_{it-1}\ \varphi) \qquad (2b)$$

$$Z_{t-1}.\varphi= \Sigma\alpha'_j\ RTEC_{ijt-1} + \Sigma\ \gamma_j'\ RIn_{ijt-1} + \theta_j'\ X_{ijt-1} + \Sigma\delta_j\ D_j \qquad (2c)$$

Where indexes 'i', 'j' and 't' correspond to firm, resource and year, respectively. In equation (1), IR_{it} is the profitability indicator; $RTEC_{ijt-1}$ are variables indicating basic technological resources; RIN_{ijt} are variables indicating intangible resources, $RTan_{ijt}$ are variables indicating tangible resources; X_{ijt} are control variables; Dj are dummy variables corresponding to three sector categories. In equation (2a), Prob is the probability function that firm 'i' has made an innovation activity in 2004 (DNN_{ijt-1}=1). Equation (2b) is the probability that firm 'i' has not made an innovation activity in 2004 (DNN_{ijt-1}=0), and equation (2c) represents variables which determine the probability of occurrence of innovation activity. In the Probit model, F represents the normal standard cumulative distribution function, while in the Logit model F is a logistic cumulative distribution function.

Equations (2a), (2b) and (2c) evaluate the impact of basic technological resources and intangibles on firm probability to implement innovation activities. This reflects the relationships between these resources and innovation results. Equation (1) represents the direct action of basic technological resources (including innovation activities and technological coordination) and other firm resources on profitability. There is an alternative interpretation for equation (1) when basic technological resources are substituted in this equation by innovation results which are estimated in equation (2a). In this case, innovating results are mediators of the impact of technological resources on firm profitability.

The three profitability indicators are defined in Table VIII.2. The variables representing basic technological resources are: (i) $DINN_1$: binary variable that takes the value 1 if the firm does innovation activities in products and/or products, and zero otherwise; (ii) $DINN_2$: binary variable that takes the value 1 if the firm does innovation activities in marketing and/or organization, and zero otherwise; (iii) R&D/A: R&D investments over total assets; (iv) INN/G: investment in innovation activities over total firm spending; (v) $DTIC_1$: binary variable which takes the value 1 if the firm has a web site, makes purchase orders or orders by the Internet, uses Internet for R&D activities, customer service or product distribution on line, and zero otherwise; $DTIC_2$: binary variable which takes the value 1 if the firm uses the Internet, and zero otherwise;[14] DCoor: binary variable which takes the value 1 if the firm has developed collaborations with other institutions, and zero otherwise.

There are three variables representing intangible resources (see Table VIII.2). The variable W/A represents human capital, X/V represents commercial resources, reputation or export capacity, and Exp (number years since firm creation) measures firm organizational resources. There are two tangible resources. The variable AF/AT represents physical resource and variable A/V corresponds to financial resources. There are two measures of firm size: L is number of workers and A is value of assets, which is also an indicator of firm tangible resources. The indebtedness variable (PAS/PAT) corresponds to firm total liabilities over total equity. These control variables are included in equation (1). Equations (2a), (2b) and (2c) include the variable organizational resources (Exp), number of workers and variables of basic technological resources. All equations include three sectoral dummy variables.[15] The data source of the basic technological variables is the national Survey of Science, Technology and Technological Innovation 2004 (CONCYTEC-INEI, 2004), and the remaining variables come from the Annual Economic Survey of the Manufacturing Sector 2005 (INEI, 2005).

[14] The ICT intensity variable was also available. The estimation results using this variable are available upon request.

[15] The first group (D1) include: Manufacture of Non-Metallic Products, Transformation of Non-Ferrous Metals, Metallic Products, Manufacture of Paper, Rubber and Plastics and Iron and Steel. The second group (D2), represents light industries and 'mature or standard' products. This group includes Textile Manufacturing, Manufacture of Clothing, Printing and Editing, Industry of Wood and Furniture, Shoe Manufacture, Leather Preparation and Various Manufactured Products. The third group (D3) represents the technology-intensive sectors. These include: Basic Chemicals, Other Chemicals, Electric Machinery, Pharmaceuticals and Medicines, Construction of Transportation Material and Construction of Non-Electric Machinery. The fourth group (D4) (not included in the estimations), corresponds to food, Beverages and Tobacco.

Table VIII.2
Firm level variables

Variables	Description
Sales	Weighted average of sales (thousand of dollars).
Value added	Weighted average of value added (thousand of dollars).
Basic variable	
R&D/A	Weighted average of R&D investments over total assets.
Profitability indicators	
Operating income	Sales plus other incomes minus total production, administrative and sales costs.
Earnings before taxes	Operating income minus administration and financial expenses plus other incomes (including financial incomes).
Net sales	Sales of final goods, subproducts and services to other entities.
Total assets	Fixed assets, stocks and current assets.
IR1	Weighted average of operating income over total assets.
IR2	Weighted average of earnings before taxes over total assets.
IR3	Weighted average of earnings before taxes over net sales.
Tangible resources	
Total liabilities	Total liabilities include value of current liabilities (taxes, wages, dividends, among others) and non-current liabilities (account to pay, future interests, among others)
Current assets	Current assets include cash resources, temporal investments, other accounts, loans, among others.
Fixed assets	Fixed assets correspond to buildings, machineries, equipments, automobiles, etc.
VA/K	Weighted average of value added over the value of equipments and machineries.
VBP/K	Weighted average of gross value of production over the value of equipments and machineries.
PAS/PAT	Weighted average of total liabilities over total equity.
A/V	Weighted average of current assets over net sales.
AF/AT	Weighted average of fixed assets over total assets.
L	Average number of employees.
K/L	Weighted average of the value of total assets per worker.
Intangible resources	
Exp	Number of years since the creation of the firm.
X/V	Weighted average of exports over net sales.
W/A	Weighted average of total wages over total assets.

Source: Author's own elaboration based on CONCYTEC-INEI (2004).

5. Estimation results

Equation (1) is estimated by using ordinary Least squares (OLS). Additionally, covariance matrix is calculated by using the adjustment of Newey and West (1987) when all variables described in the previous section are used.[16] This OLS estimation (1) tests the hypothesis of a direct impact of basic technological resources on firm profitability. Equation (2c) is estimated by using Probit and Logit models. Then, equation (1) is estimated again with OLS method including probability predictions of innovation activities from (2c). This estimation analyzes the hypothesis that basic technological resources (including technological cooperation) impact firm profitability through innovation results, which are determined by these resources, intangibles and firm size.

Table VIII.3 shows OLS estimations according to the interpretation that technological resources have a direct impact on firm profitability. The estimated coefficients for R&D/A, INN/G and $DINN_2$ are positive and statistically relevant for the three firm profitability indicators. The $DTIC_1$ indicator is also positive and statistically relevant, although less robust. The statistical relevance of technological indicators is observed in spite of collinearity problems between $DINN_2$ and basic technological resources (see Table VII.3) and among these resources.[17] Additionally, coefficients associated to the indicators of technological coordination and process and product innovations are not statistically significant. A preliminary conjecture derived from these results is that investments and activities in SCTel, and the ICT use applied to science and technology, commercial and internal activities of firms have a direct impact on profitability. On the other hand, technological coordination among firms and the sole availability of ICT do not have an impact on their profitability.[18]

[16] Table A.6 in the appendix shows the (weighted) average and standard deviations of profitability indicators by sector and firm size. The correlation coefficients among three profitability indicators are positive and statistically relevant exceeding the value of 0.98.

[17] It should be noted that correlation coefficients between coordination indicator and TIC_1 with basic technological resources were not statistically relevant.

[18] This idea is supported by additional estimations using the variable of actual use of ICT ($DTIC_1$), ICT availability ($DTIC_2$), Internet availability intensity ($INT\text{-}TIC_1$) and PC availability intensity ($INT\text{-}TIC_2$). Estimations are available upon request.

Table VIII.3

Estimation results for profitability indicators, equation (1). Ordinary least squares (OLS)

Variables	IR1						IR2						IR3					
	All	All with $DINN_1$	All with $DINN_2$	Without Coord; with $DINN_1$	Without Coord; with $DINN_2$	Without DINN	All	All with $DINN_1$	All with $DINN_2$	Without Coord; with $DINN_1$	Without Coord; with $DINN_2$	With-out DINN	All	All with $DINN_1$	All with $DINN_2$	Without coord; with $DINN_1$	Without coord; with $DINN_2$	With-out DINN
Basic technological resources																		
R&D/A	0.28***	0.28***	0.27***	0.28***	0.27***	0.30***	0.42***	0.42***	0.41***	0.42***	0.41***	0.44***	0.38***	0.39***	0.39***	0.38***	0.38***	0.43***
	(3.09)	(2.88)	(3.02)	(2.91)	(3.04)	(3.13)	(4.43)	(4.41)	(4.45)	(4.41)	(4.45)	(4.64)	(3.65)	(3.44)	(3.74)	(3.31)	(3.69)	(4.11)
DCoor	-1E-03	-1E-03	-2E-03			1E-03	-4E-04	-4E-04	-1E-03			2E-03	0.03	0.03	0.03			0.03
	(-0.07)	(-0.07)	(-0.12)			(0.06)	(-0.02)	(-0.03)	(-0.06)			(0.10)	(1.15)	(1.17)	(1.16)			(1.37)
$DINN_1$(prod)	-3E-03	7E-03		7E-03			-3E-03	7E-03		7E-03			3E-03	0.015		0.018		
	(-0.32)	(0.72)		(0.71)			(-0.25)	(0.65)		(0.66)			(0.18)	(1.11)		(1.32)		
$DINN_2$(org)	0.02*		0.02*		0.02*		0.02*		0.02*		0.02*		0.03+		0.03*		0.03*	
	(1.89)		(1.91)		(1.92)		(1.64)		(1.66)		(1.67)		(1.62)		(1.78)		(1.86)	
INN/G	0.25***	0.26***	0.25***	0.26***	0.25***	0.27***	0.19**	0.20**	0.19**	0.20**	0.19**	0.21**	0.20**	0.21**	0.20**	0.21**	0.20**	0.23**
	(2.98)	(2.94)	(2.95)	(2.94)	(2.95)	(3.06)	(2.27)	(2.26)	(2.25)	(2.26)	(2.25)	(2.35)	(2.01)	(2.00)	(2.03)	(1.97)	(2.01)	(2.08)
$DTIC_1$	0.03	0.04*	0.03	0.04*	0.03	0.04*	0.04+	0.04*	0.03	0.04*	0.03+	0.04*	0.05*	0.06*	0.05*	0.06*	0.05*	0.06*
	(1.58)	(1.73)	(1.57)	(1.73)	(1.56)	(1.73)	(1.61)	(1.74)	(1.59)	(1.74)	(1.59)	(1.73)	(1.67)	(1.78)	(1.68)	(1.80)	(1.72)	(1.73)
Intangible Resources																		
Exp	-3E-04	-3E-04	-3E-04	-3E-04	-3E-04	-3E-04	-2E-04	-1E-04	-2E-04	-1E-04	-2E-04	-1E-04	4E-04	4E-04	4E-04	3E-04	3E-04	4E-04
	(-1.01)	(-0.99)	(-1.03)	(-0.99)	(-1.03)	(-0.94)	(-0.51)	(-0.48)	(-0.53)	(-0.48)	(-0.52)	(-0.42)	(0.83)	(0.86)	(0.84)	(0.76)	(0.74)	(0.93)
X/V	-0.14	-0.14	-0.14	-0.14	-0.14	-0.14	0.08	0.08	0.08	0.08	0.08	0.08	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06
	(-1.40)	(-1.38)	(-1.39)	(-1.38)	(-1.39)	(-1.40)	(0.69)	(0.70)	(0.70)	(0.70)	(0.70)	(0.69)	(-0.53)	(-0.53)	(-0.54)	(-0.57)	(-0.59)	(-0.56)
W/A	0.14***	0.15***	0.14***	0.15***	0.14***	0.15***	0.14***	0.14***	0.14***	0.14***	0.14***	0.14***	0.06	0.07	0.06	0.07	0.07	0.07
	(3.39)	(3.48)	(3.39)	(3.48)	(3.38)	(3.50)	(3.01)	(3.12)	(3.02)	(3.11)	(3.01)	(3.13)	(1.21)	(1.26)	(1.21)	(1.30)	(1.25)	(1.27)
Size and indebtedness																		
A	1E-08***	1E-08***	1E-08***	1E-08***	1E-08***	1E-08***	2E-08***	2E-08***	2E-08***	2E-08***	2E-08***	2E-08***	4E-08***	4E-08***	4E-08***	5E-08***	5E-08***	4E-08***
	(2.75)	(2.85)	(2.76)	(2.83)	(2.72)	(2.83)	(2.98)	(3.06)	(2.99)	(3.00)	(2.92)	(3.05)	(3.62)	(3.75)	(3.64)	(3.76)	(3.65)	(3.79)
L	-2E-05	-2E-05	-2E-05	-2E-05	-2E-05	-2E-05	-3E-05	-3E-05	-3E-05	-3E-05	-3E-05	-3E-05	-5E-05*	-5E-05*	-5E-05*	-5E-05*	-5E-05*	-5E-05*
	(-1.20)	(-1.15)	(-1.21)	(-1.14)	(-1.20)	(-1.07)	(-1.49)	(-1.45)	(-1.49)	(-1.45)	(-1.49)	(-1.39)	(-1.87)	(-1.86)	(-1.88)	(-1.91)	(-1.93)	(-1.82)
PAS/PAT	-1E-03	-1E-03	-1E-03	-1E-03	-1E-03	-1E-03	-3E-03	-3E-03	-3E-03	-3E-03	-3E-03	-3E-03	-2E-03	-1E-03	-2E-03	-1E-03	-2E-03	-1E-03
	(-1.14)	(-1.04)	(-1.13)	(-1.04)	(-1.13)	(-1.06)	(-1.40)	(-1.33)	(-1.40)	(-1.33)	(-1.40)	(-1.35)	(-1.39)	(-1.23)	(-1.42)	(-1.23)	(-1.44)	(-1.31)
Tangible Resources																		
A/V	-0.02	-0.01	-0.02	-0.01	-0.02	-0.01	-0.03*	-0.03*	-0.03*	-0.03*	-0.03*	-0.03	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
	(-1.22)	(-0.93)	(-1.22)	(-0.93)	(-1.22)	(-0.89)	(-1.91)	(-1.67)	(-1.91)	(-1.65)	(-1.89)	(-1.64)	(-1.01)	(-0.94)	(-1.01)	(-0.90)	(-0.96)	(-0.93)
AF/AT	-0.03	-0.02	-0.03	-0.02	-0.03	-0.02	-0.07**	-0.07**	-0.07**	-0.07**	-0.07**	-0.07**	-0.12*	-0.12	-0.12*	-0.12	-0.12*	-0.11
	(-0.87)	(-0.74)	(-0.88)	(-0.74)	(-0.88)	(-0.72)	(-2.21)	(-2.07)	(-2.21)	(-2.07)	(-2.22)	(-2.06)	(-1.70)	(-1.63)	(-1.70)	(-1.65)	(-1.71)	(-1.63)
Sectors																		
D1	-1E-03	-0.01	-1E-03	-0.005	-1E-03	-0.005	-0.01	-0.02	-0.01	-0.02	-0.01	-0.02	0.06	0.05	0.06	0.05	0.06	0.05
	(-0.03)	(-0.16)	(-0.04)	(-0.16)	(-0.05)	(-0.14)	(-0.42)	(-0.52)	(-0.43)	(-0.52)	(-0.43)	(-0.51)	(0.82)	(0.75)	(0.82)	(0.76)	(0.84)	(0.76)
D2	0.01	0.01	0.01	0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.06	0.06	0.06	0.06	0.07	0.06
	(0.37)	(0.26)	(0.35)	(0.26)	(0.35)	(0.28)	(-0.24)	(-0.31)	(-0.25)	(-0.31)	(-0.25)	(-0.30)	(0.94)	(0.89)	(0.95)	(0.90)	(0.96)	(0.91)
D3	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	0.03	0.03	0.03	0.03	0.03	0.03
	(-0.47)	(-0.50)	(-0.50)	(-0.50)	(-0.50)	(-0.46)	(-0.86)	(-0.88)	(-0.88)	(-0.88)	(-0.88)	(-0.85)	(0.42)	(0.39)	(0.44)	(0.38)	(0.44)	(0.44)
Constant	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.06	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(1.28)	(1.27)	(1.29)	(1.27)	(1.29)	(1.25)	(1.34)	(1.34)	(1.35)	(1.34)	(1.35)	(1.32)	(-0.26)	(-0.25)	(-0.26)	(-0.25)	(-0.27)	(-0.27)
R^2-adj	0.11	0.10	0.11	0.10	0.11	0.10	0.10	0.10	0.11	0.10	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.10
F	3.36***	3.34***	3.57***	3.57***	3.82***	3.55***	3.30***	3.35***	3.52***	3.58***	3.77***	3.56***	3.21***	3.25***	3.42***	3.41***	3.59***	3.41***

Source: Author's own elaboration.

*Note: Standard errors are calculated by using Newey-West methodology. The symbol '+' is used for robust standard errors (Huber-White). * Significant at 10%; ** Significant at 5%, *** Significant at 1%*

From the remaining tangible and intangible resources and firm size, coefficients related to actual assets (A) are positive and statistically relevant in all regressions. Additionally, the proxy indicator of human resource (W/A) has a positive and statistical relevant impact on firm profitability, although less robust. The effects of organizational resources (Exp), commercial resources (export capacity) and indebtedness on profitability were not statistically relevant. With regard to coefficients of physical resources indicator (AF/AT) and financial indicator (A/V), signs and statistical relevance may have been altered by the relevant correlations between these indicators and firm assets.

Subject to data limitations and estimation methods, econometric results suggest that the empirical approach followed is relatively weak in order to explain profitability determinants in the sample of Peruvian manufacturing firms. Indeed, tangible and intangible resources and firm size only explain 11% of firm profitability variations. From the whole set of resources, technological resources —especially SCTel investments and ICT use— and size of actual assets, are the most important resources for explaining firm profitability. There are two possible hypotheses that could explain the low contribution of firm resources in explaining profitability variations. First, that profitability of Peruvian manufacturing firms reacts more to economic factors (such as prices of goods and production factors, competition degree, market structure and demand changes) than to firm capabilities and resources (specially technological and human resources). Two facts are consistent with this hypothesis: i) manufacturing production and manufacturing labor productivity are cyclically synchronized to changes in gross domestic product (Rodríguez and Tello, 2009); and ii) GDP growth rate in the last 60 years has been positively associated to investment rates with no substantive changes in total factor productivity (Távara and Tello, 2010, and Tello, 2009).

The second hypothesis is related to the absence of firms implementing SCTel activities and the low level of human capital in Peruvian firms. In the sample of 339 firms, only 13% invested in R&D activities and 44% did not invest in innovation activities. For the sample of CONCYTEC-INEI (2004) of 1,312 manufacturing firms, only 8.5% spent on R&D and 43% invested in innovation activities. Moreover, in the same sample, only 14.9% of employees had higher or post-graduate education. These facts are consistent with the absence of substantial changes in industrial productivity in Peru.

Estimations of equation (2a) are reported in Table VIII.4.[19]. The results indicate that most of the basic technological resources, including technological coordination, have a positive and relevant impact on innovation probability in products, processes, marketing and organization of manufacturing firms. These probabilities are also positively associated to firm size. The non-statistical relevance of (R&D/A) is because

[19] Estimations using indicators of ICT use intensity ($INT\text{-}TIC_1$ and $INT\text{-}TIC_2$) are available upon request.

only 7.7% of the 339 firms developed, jointly, R&D activities and innovations in marketing and organization. Instead, 40.4% of the 339 firms developed joint activities of R&D and innovations in products and processes. These results and the previous ones support the hypothesis of Surroca and Santamaría (2007), which states that technological coordination affects firm profitability only through its effects on firm innovation outcomes.

Table VIII.4
Probit and Logit estimation, equation (2c)

Variables	Product and/or process innovations ($DINN_1$)				Organizational and commercialization innovations ($DINN_2$)			
	$Probit_1$	$Probit_2$	$Logit_1$	$Logit_2$	$Probit_1$	$Probit_2$	$Logit_1$	$Logit_2$
Basic technological resources								
R&D/A	50.72***	51.28***	107.41***	111.77**	3.58	3.90	5.52	6.00
DCoor	0.93***	0.97***	1.58***	1.63***	0.46*	0.51**	0.75*	0.82**
INN/G	5.16***	4.54***	9.41***	8.94***	2.99**	2.71**	5.19**	4.78**
$DTIC_1$	0.96***		1.69***		0.80***		1.31***	
$DTIC_2$		1.06***		1.76***		0.91**		1.46**
Intangible resources and size								
Exp	0.006	0.007	0.009	0.011	0.006	0.007	0.009	0.011
L	0.0006**	0.0007***	0.0010**	0.0011**	0.0006***	0.0007***	0.001**	0.0013**
Sectors								
D1	0.40	0.49	0.69	0.85	-0.32	-0.23	-0.54	-0.36
D2	0.43	0.47	0.69	0.82	-0.23	-0.16	-0.38	-0.25
D3	0.77**	0.86***	1.25**	1.38**	0.07	0.17	0.10	0.28
Constant	-2.03***	-2.31***	-3.46***	-3.86***	-1.03***	-1.32***	-1.66***	-2.13***
R^2-McFadden	0.20	0.18	0.21	0.19	0.1	0.08	0.1	0.08
LR statistic	93.4***	85.07***	94.86***	86.65***	44.54***	38.59***	44.64***	38.75***
N	339	339	339	339	339	339	339	339

Source: Author's own elaboration.
*Note: * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Estimations of equation (1) using (predicted) innovation probabilities from the Probit[20] model and the indicator $DTIC_1$, are shown in Table VII.5.[21] The results show that, except for innovation probabilities in processes, products, marketing and organization, basic technological resources lose statistical robustness compared to estimations including indicators $DINN_1$ and $DINN_2$. A possible explanation is the correlation between estimated

[20] The outcomes with the probabilities estimated with the Logit model are similar and they are not reported.
[21] Estimation using indicators $DTIC_2$, INT-TIC_1 and INT-TIC_2 are available upon request.

probabilities and technological variables. However, in the OLS estimations, these correlations were present and they did not prevent coefficients associated to variables I&D/A, INN-G and $DTIC_1$ from being statistically relevant. An alternative explanation is that innovation probabilities collect all relevant information from basic technological resources and, therefore, it is through the occurrence of innovation outcomes that these basic technological resources impact profitability levels.[22] An outcome that supports this conjecture is that R^2-adj for practically all estimations is higher when only innovation probabilities are included in the regressions.

The outcomes related to intangible and tangible resources, indebtedness and firm size in terms of assets remain the same as with OLS method. Nevertheless, unlike these, in the estimations including innovation probabilities, firm size has a statistical and relevant impact, although with a negative sign, on firm profitability. The sign differences in coefficients related to assets and firm size suggest that firm capital (or assets) intensity per worker affects profitability positively.

Summing up, within the theory of firm resources and capabilities, the empirical evidence discussed supports the hypothesis that technological resources, such as activities and investments in SCTeI and ICT use (actually applied in the productive and commercial activities), together with size of assets and human capital, are the most important resources impacting on profitability of Peruvian manufacturing firms. Furthermore, results show, although not conclusively due to data limitations and methods used, that technological resources affect profitability through their impacts on innovation probabilities. On the other hand, the low inclination of manufacturing firms towards developing activities and investing in SCTeI and the low level of human capital within firms, indicate that firm profitability may depend on a higher proportion on other aggregate economic factors. The low growth of industrial productivity in Peru is consistent with the insufficient emphasis of firms towards SCTeI activities and ICT use.

[22] It should be emphasized that variable $DINN_1$ was not statistically relevant in OLS regressions, but it was statistically relevant when regressions were estimated including innovation probabilities in products and processes.

Table VIII. 5
Estimation results for profitability indicators, equation (1). OLS with innovation probability

Variables	IR1						IR2						IR3					
	All with DINN$_1$	All with DINN$_2$	Without coord; with DINN$_1$	Without coord; with DINN$_2$	Only DINN$_1$	Only DINN$_2$	All with DINN$_1$	All with DINN$_2$	Without coord; with DINN$_1$	Without coord; with DINN$_2$	Only DINN$_1$	Only DINN$_2$	All with DINN$_1$	All with DINN$_2$	Without coord; with DINN$_1$	Without coord; with DINN$_2$	Only DINN$_1$	Only DINN$_2$
Basic technological resources																		
R&D/A	0.09	-0.14	0.18*	0.13			0.21	0.03	0.31***	0.28*			0.20	-0.05	0.20	0.11		
	(0.50)	(-0.63)	(1.73)	(0.90)			(1.26)	(0.11)	(2.99)	(1.73)			(1.14)	(-0.20)	(1.33)	(0.66)		
DCoor	-0.03	-0.06*					-0.03	-0.05					2E-03	-0.03				
	(-0.85)	(-1.84)					(-0.88)	(-1.44)					(0.05)	(-1.00)				
P(DINN$_1$)	0.08		0.05		0.11***		0.09		0.05		0.11***		0.09		0.09*		0.14***	
	(1.15)		(1.05)		(3.40)		(1.23)		(1.16)		(3.27)		(1.23)		(1.78)		(3.35)	
P(DINN$_2$)		0.35**		0.14		0.17***		0.33*		0.13		0.17***		0.39**		0.26**		0.24***
		(2.30)		(1.64)		(3.49)		(1.74)		(1.41)		(3.11)		(2.22)		(2.32)		(3.01)
INN/G	0.15	-0.10	0.21*	0.13			0.08	-0.14	0.14	0.07			0.10	-0.17	0.10	-0.04		
	(1.09)	(-0.54)	(1.88)	(1.01)			(0.54)	(-0.65)	(1.23)	(0.53)			(0.60)	(-0.84)	(0.70)	(-0.28)		
DTIC$_1$	0.02	-0.06	0.03	0.00			0.02	-0.05	0.03	0.00			0.04	-0.04	0.04	-0.01		
	(0.57)	(-1.29)	(1.03)	(-0.02)			(0.59)	(-0.88)	(1.05)	(0.11)			(1.01)	(-0.83)	(1.09)	(-0.21)		
Intangible resources																		
Exp	-5E-04	-1E-03**	-4E-04	-6E-03*	-5E-04*	-7E-04**	-4E-04	-1E-03*	-2E-04	-4E-04	-3E-04	-5E-04	2E-04	-6E-04	1E-04	-2E-04	1E-04	-2E-04
	(-1.59)	(-2.34)	(-1.34)	(-1.69)	(-1.82)	(-2.11)	(-1.24)	(-1.79)	(-0.89)	(-1.26)	(-1.17)	(-1.52)	(0.30)	(-0.92)	(0.32)	(-0.50)	(0.22)	(-0.40)
X/V	-0.15	-0.15	-0.14	-0.14	-0.15	-0.14	0.07	0.07	0.08	0.08	0.07	0.08	-0.07	-0.07	-0.07	-0.06	-0.07	-0.06
	(-1.45)	(-1.53)	(-1.39)	(-1.40)	(-1.44)	(-1.45)	(0.60)	(0.63)	(0.67)	(0.71)	(0.65)	(0.70)	(-0.63)	(-0.64)	(-0.63)	(-0.58)	(-0.66)	(-0.59)
W/A	0.15***	0.15***	0.14***	0.15***	0.14***	0.15***	0.14***	0.15***	0.14***	0.14***	0.14***	0.14***	0.07	0.07	0.07	0.07	0.06	0.07
	(3.50)	(3.70)	(3.43)	(3.49)	(3.37)	(3.56)	(3.13)	(3.30)	(3.07)	(3.12)	(3.06)	(3.20)	(1.27)	(1.39)	(1.26)	(1.33)	(1.23)	(1.38)
Size and indebtedness																		
A	2E-08***	2E-08***	1E-08***	1E-08***	1E-08***	1E-08***	2E-08***	2E-08***	2E-08***	2E-08***	2E-08***	2E-08***	4E-08***	4E-08***	4E-08***	4E-08***	4E-08***	4E-08***
	(3.04)	(3.08)	(2.73)	(2.60)	(2.69)	(2.82)	(3.33)	(3.58)	(2.97)	(2.88)	(2.99)	(3.08)	(3.95)	(4.12)	(3.75)	(3.71)	(3.59)	(3.72)
L	-3E-5*	-6E-5***	-2E-5	-3E-5**	-3E-5*	-4E-5***	-4E-5**	-7E-5***	-3E-5*	-4E-5***	-4E-5**	-5E-5***	-6E-5**	-1E-4***	-6E-5**	-8E-5***	-6E-5**	-8E-5***
	(-1.72)	(-2.74)	(-1.47)	(-2.45)	(-1.96)	(-2.74)	(-2.18)	(-2.78)	(-1.83)	(-2.73)	(-2.18)	(-2.75)	(-2.46)	(-3.79)	(-2.33)	(-3.02)	(-2.52)	(-2.95)
PAS/PAT	-1E-03	-1E-03	-1E-03	-1E-03	-1E-03	-1E-03	-2E-03	-2E-03	-2E-03	-2E-03	-2E-03	-2E-03	-1E-03	-1E-03	-1E-03	-1E-03	-1E-03	-1E-03
	(-1.02)	(-1.03)	(-1.04)	(-1.04)	(-1.03)	(-1.09)	(-1.32)	(-1.34)	(-1.33)	(-1.34)	(-1.33)	(-1.37)	(-1.26)	(-1.27)	(-1.26)	(-1.28)	(-1.23)	(-1.32)
Tangible resources																		
A/V	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.03	-0.03*	-0.03*	-0.03*	-0.03*	-0.03*	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
	(-0.83)	(-1.00)	(-0.93)	(-1.06)	(-1.17)	(-1.16)	(-1.61)	(-1.75)	(-1.68)	(-1.79)	(-1.94)	(-1.92)	(-0.91)	(-0.97)	(-0.91)	(-0.98)	(-0.97)	(-0.98)
AF/AT	-0.02	-0.03	-0.02	-0.02	-0.02	-0.03	-0.07**	-0.07**	-0.07**	-0.07**	-0.07**	-0.07**	-0.11	-0.12*	-0.11	-0.12*	-0.11*	-0.12*
	(-0.75)	(-0.85)	(-0.73)	(-0.76)	(-0.76)	(-0.82)	(-2.09)	(-2.16)	(-2.07)	(-2.09)	(-2.12)	(-2.18)	(-1.64)	(-1.68)	(-1.64)	(-1.66)	(-1.66)	(-1.69)
Sectors																		
D1	-0.01	0.04	-0.009	0.011	-0.01	0.01	-0.02	0.02	-0.02	-1E-03	-0.02	2E-03	0.04	0.10	0.04	0.08	0.05	0.08
	(-0.35)	(1.04)	(-0.28)	(0.34)	(-0.30)	(0.41)	(-0.71)	(0.60)	(-0.64)	(-0.04)	(-0.63)	(0.06)	(0.63)	(1.36)	(0.64)	(1.17)	(0.70)	(1.09)
D2	2E-3	0.04	5E-3	0.02	4E-3	0.02	-0.02	0.02	-0.01	-4E-4	-0.01	3E-4	0.05	0.09	0.05	0.08	0.06	0.08
	(0.07)	(1.01)	(0.15)	(0.57)	(0.12)	(0.58)	(-0.51)	(0.41)	(-0.43)	(-0.01)	(-0.45)	(0.01)	(0.78)	(1.28)	(0.79)	(1.17)	(0.83)	(1.08)
D3	-0.03	-0.03	-0.03	-0.02	-0.03	-0.02	-0.05	-0.04	-0.04	-0.03	-0.05	-0.04	0.01	0.02	0.01	0.02	0.01	0.02
	(-0.89)	(-0.74)	(-0.72)	(-0.58)	(-0.95)	(-0.65)	(-1.21)	(-1.07)	(-1.10)	(-0.95)	(-1.32)	(-1.01)	(0.14)	(0.28)	(0.14)	(0.33)	(0.11)	(0.32)
C	0.06	5E-4	0.05	0.03	0.06*	0.02	0.06+	0.01	0.06	0.04	0.07*	0.03	-0.02	-0.08	-0.02	-0.06	-4E-3	-0.06
	(1.39)	(0.01)	(1.34)	(0.73)	(1.66)	(0.57)	(1.45)	(0.19)	(1.40)	(0.83)	(1.76)	(0.70)	(-0.20)	(-0.81)	(-0.20)	(-0.65)	(-0.05)	(-0.63)
R2	0.10	0.11	0.10	0.11	0.10	0.11	0.10	0.11	0.11	0.11	0.11	0.11	0.10	0.10	0.10	0.10	0.10	0.11
F	3.46***	3.70***	3.64***	3.71***	4.21***	4.50***	3.48***	3.63***	3.65***	3.70***	4.32***	4.50***	3.28***	3.43***	3.50***	3.63***	4.23***	4.55***

Source: Author's own elaboration.
*Note: Standard errors are calculated by using Newey-West methodology. The symbol '+' is used for robust standard errors (Huber-White). * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

6. Concluding remarks

This study reports several indicators of science and technology, innovation and technological coordination and ICT use in Peru. Within a firm level framework, empirical evidence has been presented on some potential relationships between technological indicators and profitability for a sample of 339 manufacturing firms. The indicators are consistent with the usual presumption of weak technological development and low priority given to activities of science, technology and innovation in Peru. In 2007, Peru invested 0.1 cents per dollar in R&D; from a total of 4,861 firms in 2004, only 4.5% developed science and technology activities investing 0.3 cents per dollar of general spending, 34.8% implemented innovation activities investing 0.7 cents per dollar of sales; and 5.2% developed activities of collaboration or cooperation in innovation activities with other institutions.

On the other hand, empirical evidence shows that technological resources associated to SCTeI activities significantly affects firm profitability. Additionally, results suggest, although in a non-conclusive way, that it is through innovation activities that these resources affect firm profitability. Second, intangible and tangible resources and firm employment also have a relevant impact on profitability. The impact of both resources is positive and the impact of employment is negative. Third, empirical evidence suggests a low explanation power of analyzed resources. This suggests that economic factors associated to good prices and production factors, and demand changes (internal and external) may have contributed in a higher proportion to profitability than firm resources, particularly technological ones. It may be assumed that economic performance of manufacturing firms (and probably of most economy sectors) of Peru, has been more associated to changes in those economic basis than to changes in technological resources. The evidence discussed here, and also empirical evidence on low industrial productivity growth in Peru (Rodríguez and Tello, 2010; Távara and Tello, 2009; and Tello, 2009), are consistent with this hypothesis.

In sum, in order to obtain sustained and sustainable growth in Peru, it is essential to generate an environment and incentives which enable a greater preponderance of science, technology, and ICT use within firm activities.

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8. Appendix

Table A.1
ICT indicators in Peru

Sector	N[a]	Percentage of firms with:						Internet Use		Number of computers	
		PC's	Internet	Intranet	Extranet	Web site	Internet orders[b]	Products and processes information	Customer service	By firm	By employees
Primary	362	89.3	71.3	15.3	4.4	17.5	26.6	62.3	22.7	27	0.23
Manufacturing	1 459	92.4	78.5	17.9	5.7	30	42.6	72.4	38.5	23	0.29
Processed minerals	343	95.1	86.5	18.4	4.7	36.9	50	80	47.5	20	0.29
Traditional manufacturing	371	92.6	77.5	20.6	7.3	30.6	43.9	71.6	40.8	21	0.22
Technological	439	92.6	78	16.1	6.1	29.4	41.4	72.5	36.1	22	0.37
Food	306	88.9	71.7	16.8	4.2	22.5	34.3	65	28.9	29	0.29
Technological	505	85.2	71.6	21.1	10	30.6	27	62.1	35.7	49	0.74
Services	2 363	90.6	76.2	19.9	7.8	29.9	36.5	66	37.8	30	0.43
Total 2004	4 688	90.5	76.1	19.1	7.1	29.1	36.6	67.3	36.6	29	0.39
Total 2007[c]	1 277	79.3	75.2	19.9	6.9	40	51	73.3	44.8	19	0.21

Source: Author's own elaboration based on CONCYTEC-INEI (2004) and INEI (2007).
[a] N corresponds to the average number of firms.
[b] If the firm received purchase orders from other entities or if the firm requests goods or services to other firms by Internet.
[c] In the Survey 2007 there is no sectoral information on firms.

Table A.2
Innovation indicators in Peru[1]
(Percentages)

Sectors-Firms	Number of firms	S-ACT	ACT		Human capital		Innovation activities						Coordination	
		Yes	G-ACT	G-R&D	Post-graduate	Superior	S_INN	SINN_prod	SINN_org	INN/V	No INN	INN-RP	DCoord	Coord-U/CI
Primary	349	4.3	0.8	0.7	0.9	13.4	35.2	30.1	21.5	0.8	35	98.2	7.7	5.2
Mega	18	11.1	1.3	1.1	1.1	15.2	50.0	50.0	16.7	0.4	4	100.0	16.7	16.7
Large	57	7.0	0.6	0.5	0.9	13.5	49.1	45.6	33.3	2.4	11	100.0	14.0	8.8
Medium	92	2.2	0.1	0.1	1.4	19.1	45.7	38.0	32.6	0.4	13	95.2	6.5	4.3
Small	182	3.8	0.1	0.0	1.8	29.1	24.2	19.2	12.7	0.4	14	100.0	5.5	3.3
Manufacturing and construction	1 529	7.6	0.6	0.4	1.3	14.7	40.9	35.5	28.3	0.6	433	96.8	6.6	7.4
Mega	55	16.4	0.5	0.4	1.2	16.8	65.4	60.0	56.3	0.5	30	97.3	14.5	6.2
Large	165	24.8	1.1	0.7	1.5	20.2	67.3	60.0	48.5	0.6	93	99.0	10.9	7.1
Medium	382	10.2	0.2	0.1	1.1	21.7	51.3	44.0	37.2	0.4	155	96.4	9.2	2.1
Small	927	2.9	0.2	0.1	1.5	23.0	30.4	26.2	19.5	0.6	168	96.2	4.3	3.8
Technological	524	2.5	0.1	0.1	2.0	24.1	31.5	21.2	25.6	1.3	92	99.5	4.4	1.7
Mega	22	22.7	0.1	0.0	1.9	30.2	72.7	72.7	59.1	0.7	3	100.0	13.6	4.6
Large	53	7.5	1.3	1.3	3.4	30.0	66.1	56.6	49.0	1.0	12	97.1	11.3	9.4
Medium	132	1.5	0.0	0.0	1.2	23.8	40.1	25.7	31.1	0.3	26	100.0	6.8	2.3
Small	353	1.2	0.0	0.0	1.9	21.0	23.2	13.6	19.9	6.9	48	100.0	2.0	0.3
Services and commerce	2 459	3.0	0.3	0.1	1.3	25.0	31.6	20.3	26.5	1.8	237	95.2	4.0	2.1
Mega	70	8.6	0.4	0.0	0.8	22.8	45.7	31.4	37.1	0.7	8	93.2	8.6	4.3
Large	170	6.5	0.5	0.2	1.7	26.7	51.7	38.8	43.5	0.4	25	98.3	6.5	3.5
Medium	526	4.6	0.1	0.0	2.2	27.1	46.2	30.6	38.0	0.6	59	95.7	6.5	4.2
Small	1 657	1.8	0.2	0.1	1.9	27.3	23.7	14.0	20.2	0.6	150	94.1	2.7	1.2
Total mega	165	13.3	0.3	0.2	1.1	20.0	56.5	39.4	37.1	0.5	82	96.3	12.4	6.5
Total large	445	13.5	0.5	0.3	1.7	22.6	59.1	36.2	39.3	0.7	238	98.3	9.8	6.2
Total medium	1 132	5.9	0.1	0.1	1.7	23.7	47.1	24.8	26.5	0.4	460	96.5	7.4	4.8
Total small	3 119	2.2	0.1	0.0	1.7	25.6	25.7	13.6	13.2	1.3	662	95.9	3.3	1.5
Total	4 861	4.5	0.3	0.2	1.4	21.8	34.8	19.2	19.5	0.7	1 442	96.5	5.2	2.9

Source: Author's own elaboration based on Concytec-INEI (2004). The variables used are the following: S-ACT: percentage of firms involved in science and technology activities; Human capital: weighted average of the percentage of employees with higher and post-graduate education; G-ACT: spending in science and technology activities over total spending; G-R&D: R&D investments over total spending; S-INN: percentage of firms which innovated in processes, products, organization or marketing; DINN_prod: percentage of firms which have made product or process innovations; DINN_org: percentage of firms which have made marketing and/or organizational innovations; INN/V: weighted average of investments in innovation activities over total net sales; N_INN : number of innovating firms; INN-RP: percentage of innovating firms financed with own resources; Dcoord: percentage of firms which have collaborated or coordinated with other entities in innovation activities; Coord-U/CI: percentage of firms that coordinated with universities, technical institutes, research centers, science and technology institutions with innovation purposes.

Table A.3

Innovation indicators in manufacturing sector in Peru[a]

(Percentages)

Description	Number of firms	S-ACT	ACT		Human capital		Innovation activities									Coordination		
			G-ACT	R&D/G	Post-graduate	Superior	S_INN		SINN_prod		SINN_org		INN/V	No INN	INN-RP	DCoord[11]		Coord-U/CI
Processed minerals	359	10.3	1.4	0.8	1.2	16.0	44.8	(59.5)	40.4	(42.7)	28.7	(34.4)	1.3	34.5	96.9	7.8	(11.5)	3.6
Mega	10	10.0	16.4	10.3	1.6	16.1	70.0	(66.7)	70.0	(33.3)	50.0	(33.3)	2.4	1.8	100.0	40.0	(42.9)	20.0
Large	51	27.4	1.4	0.5	1.2	14.2	72.5	(70.7)	64.7	(53.7)	53.0	(46.3)	1.3	6.4	100.0	15.7	(15.6)	5.9
Medium	120	13.4	0.3	0.2	1.2	19.6	51.7	(59.6)	45.8	(48.1)	33.4	(34.6)	0.8	14.0	93.6	8.3	(10.7)	4.2
Small	178	3.4	1.1	1.0	1.8	23.0	30.9	(43.8)	28.1	(21.9)	17.4	(18.8)	0.2	14.5	96.3	3.4	(2.8)	1.7
Traditional manufacturing	406	3.7	0.1	0.0	0.6	15.5	39.2	(53.6)	33.0	(39.2)	28.6	(40.2)	0.3	26.6	95.5	6.6	(8.2)	3.4
Mega	15	13.3	0.0	0.0	0.2	10.9	80.0	(70.6)	80.0	(58.8)	80.0	(70.6)	0.3	4.0	100.0	0.0	(0.0)	0.0
Large	42	11.9	0.1	0.1	0.8	17.7	47.6	(66.7)	42.9	(58.3)	38.1	(54.2)	0.2	3.6	94.8	9.5	(13.0)	7.1
Medium	90	4.4	0.1	0.1	0.9	15.4	45.6	(57.7)	35.6	(34.6)	36.7	(30.8)	0.9	7.9	97.6	11.1	(18.5)	8.9
Small	259	1.5	0.0	0.0	0.7	17.4	33.2	(30.0)	27.8	(16.7)	21.2	(20.0)	0.4	12.8	94.5	5.0	(0.0)	1.1
Technological	230	15.2	0.7	0.6	1.8	20.5	48.3	(74.7)	43.0	(53.2)	34.3	(49.4)	0.7	18.8	99.4	5.6	(6.3)	4.8
Mega	5	40.0	0.5	0.5	1.6	15.9	60.0	(100.0)	60.0	(100.0)	3.8	(100.0)	0.3	1.0	60.0	20.0	(0.0)	20.0
Large	35	37.1	0.8	0.7	2.0	20.4	77.1	(87.0)	71.4	(52.2)	26.9	(43.5)	0.8	4.4	100.0	2.9	(0.0)	2.9
Medium	71	18.3	0.5	0.3	2.1	23.6	66.2	(79.4)	60.6	(58.8)	31.3	(58.8)	0.9	8.4	98.5	9.9	(8.8)	8.5
Small	119	5.9	0.4	0.4	0.6	23.6	28.6	(44.4)	23.5	(33.3)	13.8	(27.8)	0.5	7.0	97.5	3.4	(10.5)	2.5
Food	317	7.6	1.2	1.2	1.1	16.0	41.0	(41.9)	35.6	(16.1)	26.2	(32.3)	0.7	28.2	96.8	7.6	(3.2)	5.0
Mega	19	21.1	1.0	0.9	1.1	14.6	57.9	(50.0)	42.1	(50.0)	42.1	(50.0)	0.3	2.4	77.2	15.8	(0.0)	5.3
Large	30	26.7	7.8	7.7	0.9	18.6	70.0	(100.0)	63.3	(40.0)	50.0	(80.0)	2.5	5.0	100.0	13.3	(0.0)	13.3
Medium	71	8.5	0.2	0.1	1.3	19.7	43.7	(37.5)	38.0	(0.0)	29.6	(37.5)	0.3	8.6	96.3	9.8	(0.0)	7.0
Small	197	3.1	0.1	0.1	0.9	22.4	34.0	(25.0)	30.0	(12.5)	19.8	(12.5)	0.3	14.6	97.8	5.1	(5.6)	3.1
Total mega	49	18.4	0.6	0.5	1.2	17.8	67.3	(72.4)	61.2	(58.6)	57.1	(65.5)	0.6	33.0	97.0	16.3	(14.3)	7.0
Total large	158	25.3	1.1	0.7	1.4	19.6	66.5	(75.3)	60.1	(53.8)	46.8	(49.5)	0.6	97.0	99.0	10.8	(9.5)	6.8
Total medium	352	11.1	0.2	0.1	1	20.9	51.4	(63.3)	44.6	(45.0)	36.4	(40.8)	0.4	167.0	97.0	9.7	(11.3)	2.0
Total small	753	3.1	0.2	0.1	1.2	16.5	32.1	(36.1)	27.8	(20.6)	20.1	(19.6)	0.2	200.0	96.0	4.4	(3.6)	4.1
Total	1312	8.5	0.7	0.5	1.2	13.7	42.8	(59.6)	37.4	(41.6)	29.0	(39.2)	0.6	497.0	97.0	7.0	(8.6)	4.0

Source: Author's own elaboration based on Concytec-INEI (2004). The variables used are the following: S-ACT: percentage of firms involved in science and technology activities; Human capital: weighted average of the percentage of employees with higher and post-graduate education; G-ACT: percentage of spending in science and technology activities of total spending; G-R&D: percentage of investment in research and development of total firm spending; S-INN: percentage of firms which innovated in processes, products, organization or marketing; DINN_prod: percentage of firms which have made product or process innovations; DINN_org: percentage of firms which have made marketing and/or organizational innovations; INN/V: weighted average of the percentage of investment in innovation activities of total net sales; N_INN : number of innovating firms; INN-RP: percentage of innovating firms financed with own resources; Dcoord: percentage of firms which have collaborated or coordinated with other entities in innovation activities; Coord-U/CI: percentage of firms that coordinated with universities, technical institutes, research centers, science and technology institutions with innovation purposes.

[a] *Figures in brackets correspond to the sample of 339 firms for which there is data available for the profitability analysis in the next section.*

Table A.4

ICT, science and technology and economic performance indicators

(Percentages)

Sectors	Yes/No	Sales[a]	Value added[a]	Basic variable	Profitability indicators			Tangible resources							Intangible resources	
				R&D/A	IR1	IR2	IR3	VA/K	VBP/K	PAS/PAT	A/V	AF/AT	L	K/L[a]	X/V	W/A
ICT: Firms that have or have not computers																
Processed minerals	Yes	18 923	5 114	0.3	10.0	9.2	9.5	26.2	94.0	114.4	49.1	52.2	170	102.1	31.3	23.8
	No	213	123	0.0	4.1	0.8	0.5	94.3	185.3	48.8	19.2	67.8	15	8.9	0.0	0.0
Technological	Yes	12 841	3 622	0.9	9.0	6.9	6.7	29.0	98.3	107.9	48.9	49.7	131	89.1	18.4	37.2
	No	213	41	0.0	3.6	3.2	2.0	30.8	139.1	391.3	35.8	5.9	11	6.8	0.0	98.0
Food	Yes	15 214	4 693	0.0	5.2	-1.2	-1.3	27.4	88.2	113.6	33.0	70.5	145	129.3	0.6	11.7
	No	490	130	0.0	22.9	24.5	3.0	214.6	714.1	108.6	6.4	43.1	30	3.3	0.0	26.7
Total	Yes	16 488	4 575	0.3	9.2	7.4	7.6	27.7	94.4	112.7	47.3	53.8	154	101.5	24.6	23.1
	No	323	93	0.0	8.3	7.6	2.4	89.9	285.8	158.9	15.8	30.2	19	5.0	0.0	35.3
ICT: Firms that have or have not Internet																
Processed minerals	Yes	19 439	5 250	0.3	10.0	9.2	9.5	26.2	93.8	114.6	49.2	52.3	173	102.7	31.3	23.7
	No	2 693	830	0.0	16.8	13.8	9.6	44.3	165.9	76.8	39.7	43.1	55	47.1	21.4	35.7
Traditional manufacturing	Yes	13 316	4 075	0.0	8.2	6.5	6.7	29.7	96.2	114.2	52.2	49.3	305	43.8	38.2	18.7
	No	585	350	0.0	7.1	3.3	2.6	74.9	184.9	82.2	46.2	15.1	19	10.1	0.0	29.3
Technological	Yes	13 550	3 818	0.9	9.1	6.9	6.7	29.0	98.4	108.5	48.8	49.7	137	89.5	18.4	37.2
	No	357	141	0.0	1.3	4.6	8.0	23.0	61.3	22.9	80.9	45.2	15	26.5	0.0	37.7
Food	Yes	8 995	3 272	0.0	16.2	15.3	14.4	38.7	105.0	65.1	41.8	55.0	81	103.2	0.5	22.9
	No	25 764	6 837	0.0	-1.1	-10.6	-13.5	20.9	78.8	156.6	26.0	79.4	262	144.0	0.7	9.8
Total	Yes	15 530	4 432	0.2	9.5	8.3	8.4	28.1	95.7	111.1	49.6	51.1	199	73.2	29.3	23.2
	No	10 409	2 830	0.0	-0.5	-9.6	-11.9	22.0	81.9	149.3	27.4	77.5	117	126.9	1.8	10.3
ICT: Firms that use or not the Internet in R&D activities																
Processed minerals	Yes	24 938	6 597	0.4	11.0	10.4	9.7	28.4	104.4	130.8	47.5	49.0	218	90.7	36.8	19.6
	No	11 267	3 227	0.0	8.0	6.8	9.0	21.9	73.4	87.9	53.8	58.8	107	131.3	15.8	32.9
Traditional manufacturing	Yes	19 968	6 142	0.0	8.9	7.7	7.8	30.3	97.9	111.7	50.9	49.9	438	42.7	39.0	20.2
	No	5 367	1 632	0.0	5.5	2.2	2.4	27.7	90.3	123.8	57.8	46.9	143	47.6	34.0	15.4
Technological	Yes	17 508	4 821	1.0	8.9	6.8	6.7	28.0	97.6	109.2	48.7	50.4	164	99.9	18.9	36.3
	No	3 696	1 265	0.0	10.2	7.4	6.6	38.5	105.0	95.4	50.1	43.1	66	36.2	13.3	42.3
Food	Yes	51 000	13 522	0.0	-0.6	-9.4	-11.8	21.0	79.1	141.9	26.4	78.9	540	136.1	0.8	10.8
	No	6 532	2 474	0.0	18.3	17.4	15.8	41.8	109.3	68.5	43.5	51.5	53	108.8	0.5	18.2
Total	Yes	22 179	6 165	0.3	9.0	7.2	7.1	28.2	99.0	121.4	47.2	52.0	275	73.1	31.0	20.4
	No	7 438	2 290	0.0	8.7	7.1	8.3	26.3	82.8	92.4	52.9	54.6	103	83.5	17.5	23.4
ICT: Firms that use or not the Internet to customer service																
Processed minerals	Yes	17 879	6 073	0.1	12.2	12.0	14.8	27.6	83.9	77.1	56.7	53.9	133	145.2	9.3	22.3
	No	20 053	4 075	0.8	6.9	5.3	4.4	24.3	108.5	206.9	41.9	49.9	209	72.3	52.6	26.9
Traditional manufacturing	Yes	14 918	4 677	0.0	9.3	7.6	7.9	30.1	96.2	117.5	52.4	49.6	299	48.5	35.0	24.3
	No	10 368	3 062	0.0	6.3	4.7	4.8	29.1	96.7	108.6	51.9	48.6	286	38.1	43.1	14.6
Technological	Yes	15 821	4 290	1.1	9.6	7.2	7.0	27.9	101.6	107.6	46.9	51.8	144	110.6	23.6	39.0
	No	9 337	2 830	0.6	8.0	6.1	6.0	31.1	91.7	108.6	52.8	45.7	116	57.6	7.9	35.1
Food	Yes	45 341	15 066	0.0	5.3	-2.3	-2.7	27.7	82.6	110.3	29.9	75.1	421	150.6	0.7	11.5
	No	4 290	978	0.0	4.7	4.1	3.6	26.1	114.9	130.6	43.0	49.3	47	60.6	0.4	37.1
Total	Yes	17 627	5 585	0.2	10.2	8.3	9.3	28.3	90.2	95.1	50.4	54.9	200	94.4	18.3	21.7
	No	12 929	3 106	0.3	6.8	5.2	4.7	26.7	103.0	153.3	45.8	48.8	189	55.5	41.3	20.4
Innovation: Firms that develop or not science and technology activities																
Processed minerals	Yes	30 933	11 626	0.9	16.5	16.4	18.5	33.3	98.3	65.5	56.8	49.6	198	147.7	5.6	15.8
	No	16 578	3 848	0.0	7.3	6.3	6.3	23.3	92.4	143.1	46.4	53.4	162	92.2	40.5	28.2
Traditional manufacturing	Yes	18 667	6 344	0.1	8.9	5.7	6.0	32.1	84.5	99.8	58.8	44.4	318	56.6	10.4	27.3
	No	12 455	3 771	0.0	8.1	6.6	6.8	29.5	97.9	116.0	51.4	49.8	294	42.6	41.4	17.9
Technological	Yes	14 136	4 525	2.1	6.4	5.8	5.5	34.1	109.1	96.4	51.5	45.1	216	46.3	10.5	42.4
	No	11 758	3 126	0.0	10.0	7.2	7.1	26.8	93.5	112.8	47.8	51.6	96	122.6	21.6	33.5
Food	Yes	822	262	0.9	-1.9	11.6	13.8	26.9	87.8	27.1	74.1	37.5	19	61.3	0.0	11.0
	No	14 677	4 526	0.0	5.2	-1.2	-1.3	27.4	88.4	113.9	32.8	70.6	141	127.7	0.6	11.7
Total	Yes	21 518	7,660	1.1	13.1	12.5	13.4	33.4	99.2	75.9	55.6	47.9	219	86.7	7.6	26.0
	No	14 093	3 744	0.0	7.8	5.7	5.8	26.1	93.6	126.2	46.6	54.1	188	73.5	33.3	20.1
Innovation: Firms that implement or not innovation activities																
Processed minerals	Yes	28 293	7 869	0.4	11.3	11.0	10.6	28.8	100.9	95.7	46.9	51.4	216	122.9	31.8	20.9
	No	7 781	2 556	0.0	7.2	6.5	10.8	19.6	59.0	104.9	62.7	62.5	99	137.4	16.8	31.6
Traditional manufacturing	Yes	16 026	5 294	0.0	8.8	6.8	7.5	30.0	90.6	121.6	55.8	49.2	367	47.2	31.6	20.8
	No	9 263	2 427	0.0	6.7	5.9	5.4	29.0	109.4	98.7	45.5	49.2	213	37.2	50.4	13.7
Technological	Yes	14 227	4 138	1.1	9.9	8.3	7.5	32.1	104.7	96.4	48.7	46.1	153	75.0	16.0	40.9
	No	7 099	1 642	0.0	5.6	1.1	1.5	16.8	72.8	166.0	49.7	63.5	51	207.7	31.7	21.7
Food	Yes	28 494	9 269	0.0	5.4	-1.8	-2.2	27.6	84.0	105.8	31.4	73.4	267	143.4	0.7	11.6
	No	4 108	927	0.0	3.6	3.5	3.0	26.3	117.7	188.7	40.4	50.8	45	60.0	0.5	25.5
Total	Yes	21 085	6 213	0.3	10.0	8.4	8.4	29.6	97.7	101.8	47.7	52.1	239	85.8	26.1	21.5
	No	7 722	2 168	0.0	6.6	5.4	6.8	22.2	78.6	113.2	52.3	58.2	124	79.0	31.6	20.4
Collaboration: Firm that coordinate or not with other entities																
Processed minerals	Yes	94 886	27 737	0.1	13.0	13.3	13.0	29.9	100.4	85.1	45.1	53.9	594	158.2	39.1	19.7
	No	10 195	2 834	0.4	7.6	6.5	7.8	23.3	81.1	112.7	54.6	54.2	113	104.0	17.7	24.8
Traditional manufacturing	Yes	12 076	3 972	0.0	7.3	6.8	7.2	31.3	92.7	87.5	63.2	39.9	353	35.8	19.7	31.4
	No	12 850	3 916	0.0	8.2	6.5	6.7	29.6	96.7	116.8	51.3	50.0	288	44.6	39.7	17.7
Technological	Yes	1 467	367	0.3	5.7	1.1	0.8	34.6	130.0	119.1	47.8	32.5	33	12.2	1.8	25.6
	No	13 133	3 706	0.9	9.0	6.8	6.7	28.9	97.8	107.8	48.9	49.9	133	90.2	18.4	37.5
Food	Yes	800	229	0.0	3.9	3.6	4.1	25.3	91.8	72.8	88.7	21.4	15	20.2	0.1	48.6
	No	14 677	4 527	0.0	5.2	-1.2	-1.3	27.4	88.4	113.7	32.8	70.6	141	127.8	0.6	11.7
Total	Yes	52 691	15 514	0.1	12.6	12.8	12.6	30.0	100.0	85.4	46.3	52.9	411	127.0	37.7	24.2
	No	12 091	3 516	0.2	7.8	5.7	6.1	27.0	90.5	112.8	49.6	53.9	172	74.1	22.8	20.9

Source: Author ‘s own elaboration based on Concytec-INEI 2004.

[a] *Thousands of dollars.*

Table A.5
Profitability indicators in manufacturing firms, 2005
(Percentages)

Description	IR1		IR2		IR3	
	Weighted average	Standard deviation	Weighted average	σ	Weighted average	Standard deviation
Processed minerals	10.3	9.9	9.9	10.2	10.7	10.5
Mega	9.9	5.5	10.2	5.0	10.1	11.4
Large	10.9	8.6	10.2	8.8	11.9	9.8
Medium	9.9	10.2	8.5	10.3	8.8	10.8
Small	5.5	11.6	3.1	12.1	2.6	9.7
Traditional manufacturing	8.0	9.6	6.4	10.9	6.7	10.1
Mega	8.9	11.1	7.2	13.6	7.1	9.3
Large	6.3	8.2	5.4	7.6	6.5	7.5
Medium	6.7	9.0	2.9	9.7	2.5	13.3
Small	6.0	10.5	4.3	12.8	3.4	9.2
Technological	8.9	9.9	6.6	10.2	6.5	14.5
Mega	3.9	10.3	6.5	11.5	6.1	9.2
Large	9.4	5.7	6.2	6.9	6.5	20.9
Medium	10.2	9.4	9.0	9.4	7.3	8.7
Small	6.1	13.8	4.9	14.3	3.1	14.4
Food	5.2	16.3	-1.2	16.7	-1.3	30.2
Mega	-0.3	3.6	-8.0	11.1	-9.5	12.6
Large	23.4	14.9	21.7	15.3	21.5	15.9
Medium	8.8	23.3	2.3	21.9	2.2	18.2
Small	0.7	13.1	-8.2	14.5	-10.0	38.4
Total Mega	7.9	9.7	6.5	11.7	6.5	10.2
Total Large	10.1	8.4	8.7	8.7	9.9	13.5
Total Medium	9.6	10.9	7.9	11.0	7.4	11.5
Total Small	4.9	11.8	2.6	12.9	2.1	18.4
Total	9.0	10.5	7.6	11.1	8.0	14.3

Source: Author's own elaboration based on CONCYTE-INEI (2004).

IV. Impact of ICT and innovation on industrial productivity in Uruguay

Griselda Charlo[1]

1. Introduction

Information and Communication Technologies (ICT) refers to technological progress provided by informatics, telecommunications and audiovisual technologies. Basically, these technologies provide information, and serve as tools for its processing and communication channels. This generates innovation defined as a process oriented towards the solution of productive problems (Nelson and Winter, 1982), characterized by matching productive needs and technical capabilities. In short, ICT refer to informatics, Internet and telecommunications. Since we are immersed in an information society, ICT use is increasingly common and unavoidable (Castells, 2001).

When a firm decides to implement ICT innovation projects, two main forces interact. First, the perception of those who take decisions in the firm concerning the opportunity to innovate and the presence of adequate incentives to do it, together with the perception of the capacity to innovate. In other words, it is not only convenient in terms of firm environment, but also that it is sound within the firm. On the other hand, we can identify a set of variables that firms do not control, but which also affect this decision; these are related to industry characteristics, such as market conditions and competition (Romo Murillo and Hill de Titto, 2006). Markets which are intensive in transactions of innovating products are distinguished by organizational forms regulated by institutional agreements which give a stimulus to innovation behavior (Lundvall, 1988). These "organized" markets are part of the systemic dimensions which define firm environment in the context of NIS analysis (Network Information Service) in developed countries. In less developed countries, innovation often faces a great variety of obstacles and there are a few incentives in the way markets are organized, a thing which hinders the trading of new products (Yoguel and Boscherini, 2000).

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Innovation is a productive process which relies on human resources and investment in capital assets procurement, machinery and/or equipments intended for technological development and innovation activities. If the production function at the microeconomic level is the relationship between productive factors and output, capital allocated to ICT can be taken as another productive factor, in the same way as capital, work and human capital. The relative ease of access to ICT, due to their fast price reduction and quality increase, and to the fact that they are considered general purpose technologies, have led various scholars to propose that ICT, due to their effect on cost reductions of coordination among individuals and firms, may produce a change in firm structure. Likewise, innovation also has an effect on productivity, mainly through total factor productivity but also by interacting with other factors such as capital or human capital. This innovation refers to technologically new processes and products, either at firm, local, country or global level. The emphasis on novelty does not mean to make more of the same, but to expand human knowledge frontier, observing that what is novel may also be applied at firm or country level. Therefore, when we speak about innovation, we must understand that what is new for a particular country may not be new at international level.

The characteristics of Uruguayan economy determine that firm innovation behavior has specific features that are different from empirical evidence related to developed countries. The main objective of this paper is to analyze the effects of ICT and innovation on productivity in manufacturing firms in Uruguay. We are also interested in finding out if firm's employees vary in quantity and quality in relation to the level of ICT investment and innovation. This study is organized as follows. Section 2 presents a brief literature review, and Section 3 describes the methodological and empirical approach. Section 4 shows the main features of innovation activities in Uruguay. Finally, Section 5 discusses econometric results and Section 6 concludes.

2. Literature Review

The impact of ICT has been subject to discussion since they began to be investigated three decades ago. Although it is expected that ICT investments lead to cost reductions, higher flexibility and increase in firms' competitiveness, studies undertaken during the eighties and beginning of the nineties did not find a relevant statistical relationship between investment in ICT and productivity at aggregated level. The relative easiness in the access to ICT, due to their fast price reduction and quality increase, and to the fact that they are considered general purpose technologies, have led many scholars in the nineties to propose that ICT may produce a radical change in the firm structure. This phenomenon would be similar to what happened with the steam engine, the locomotive and the telegraph during the Industrial Revolution; therefore, this stage is called the technological or digital revolution.

Nevertheless, there is no consensus on ICT effects. This can be observed in the Solow Paradox, where the Nobel Prize winner said that computers could be seen everywhere, except in productivity statistics. Indeed, several studies investigated the correlation between ICT investment and firm outcomes such as benefits or improvement in productivity. As no relevant relationship was found between these variables, these studies concluded that ICT investment did not increase productivity (see Brynjolfsson, 1993). The evidence were considered paradoxical by most authors, who explained the results through the limitations of using simple bivariate relationships (Lehr and Lichtemberg, 1999), the potential negative effect of the variety increase in productivity (Barua et al., 1991), and the lagged effect of ICT investment and its dependence on labor networks externalities, and the changes in complementary infrastructure (Becchetti *et al*., 2003).

In the second half of the nineties, with new databases and new econometric methods, a positive relationship was established between ICT investment, productivity and economic growth (Brynjolfsson and Hitt, 1996). There were several improvements in empirical studies leading to these results. First, these studies disentangled the effect on productivity by different ICT technologies (communications, software, hardware, etc.). Second, special attention was given to ICT as part of the innovation process, which has to go along with other changes so that it may evidence an important improvement in productivity. Some of these changes are investments in human capital, specially qualified labor force, and employee-oriented organizational practices. Thus, ICT investment by itself does not imply productivity gains unless it is complemented by other practices (Milgrom and Roberts, 1995). Third, a wide range of econometric methods was used, giving special attention to avoid selectivity (only a small number of firms implement innovations) and simultaneity biases (innovation may involve productivity outcomes, but a high productivity may also stimulate innovation).

In this perspective, Crepon *et al.* (1998) developed a more integral framework that considers all innovation factors, starting with the firm decision to invest in R&D, results of these efforts, and their impact on productivity. This model was used later in developing countries; the study of Benavente (2004), for the Chilean case, was the first one of this kind. The results did not find that sales resulting from innovation had an effect on productivity. In Latin America, in addition to Benavente (2004), Chudnovsky *et al.* (2006) deal with manufacturing firms in Argentina in the nineties, revealing the particular features of an economy with a very pronounced economic cycle. Sanguinetti (2004) also studies the determinants of firm innovation in Argentina, and the results suggest a positive impact of size, market share and foreign capital. Sanguinetti (2004) also identifies the effects of variables at sectoral level such as market concentration or tax rate with negative effects, and qualified labor force participation with positive effect.

Innovation is a process aiming at the solution of productive problems and it is at firm level that knowledge is generated, adapted and applied to productive purposes (Nelson and

Winter, 1982). According to this approach, innovation is a specific process for each firm and it is characterized by a high degree of uncertainty (Dosi, 1988). During the process, firm generates knowledge and applies it to the creation of new products or processes, undergoing a sequence of cumulative learning. The fact that the innovating process is specific and accumulative does not mean that there is an autarchic learning by the firm; on the contrary, the development of the innovation process depends on firm capabilities to identify their needs, opportunities and incentives offered by the environment. Thus, innovation process is seen as a systemic and interactive phenomenon which takes place among the different individuals within the organization and, at the same time, between the firm and its environment (Lundvall, 1992).

In our investigation we differentiate between product and process innovations. Product innovation refers to the production of goods or services which are technologically different or improved, that is, innovation occurs when features of a product improve. Instead, process innovation occurs when there is a significant change in the technology or production methods, or when there are significant changes in the management or organization system, process reengineering, strategic planning, quality control, etc.

3. Methodological and Empirical Approach

The National Institute of Statistics (INE, in Spanish) in cooperation with the National Agency of Research and Innovation (ANNI, in Spanish) carried out Surveys on Innovation Activities (EAI, in Spanish) to manufacturing firms in Uruguay with reference years 1998-2000, 2001-2003 and 2004-2006. In the service sector, the survey was implemented only for the period 2004-2006. Furthermore, INE carried out Structural Economic Activity Surveys (EAE, in Spanish) as an updating of the Economic Census of 1997, with annual periodicity for all the following years; and its last publication was in 2007. Using the microdata derived from both surveys (EAI and EAE), this paper studies the effects of spending in ICT and innovation on productivity and personnel employed in Uruguayan manufacturing firms. We intend to quantify the ICT effects on productivity, its relationships with innovation, either in product or process, and its effects on the quantity and qualification of firm employees. Specifically, we seek to answer the question if ICT investment replaces workers or if it displaces unskilled workers in favor of skilled workers.

This study follows the methodology proposed by Leeuwen and van der Wiel (2003), who analyzed the case of Dutch firms. These authors estimate a production function in order to estimate ICT elasticity. In the case of Uruguay, we include an additional variable to identify human capital effects on productivity. As usual in the literature, we start with a Cobb-Douglas production function at firm level, where the inputs for the production of value added (Y) are capital in ICT (KTIC), other or non-ICT capital (K), workers (L) and workers with university or technical education as an approximation of human capital (LC):

$$Y_{it} = A^* K^{\alpha}_{it} * KTIC^{\beta}_{it} * LC^{\delta}_{it} * L^{ø}_{it} \qquad (1)$$

The sub-indexes i and t refers to firm and year, respectively. If we divide both sides of the equation by the number of workers L and taking logarithms, the equation for the production per worker is expressed as follows:

$$y_{it} – l_{it} = a + \alpha (k_{it} – l_{it}) + \beta (ktic_{it} - l_{it}) + \delta (lc_{it} – l_{it}) + øl_{it} \qquad (2)$$

This equation is estimated econometrically by taking the cross products of innovation with the factors corresponding to ICT capital, non-ICT capital and human capital as follows:

$$y_{it} – l_{it} = \beta_0 + \beta_1 (k_{it} – l_{it}) + \beta_2 N_i (k_{it} – l_{it}) + \beta_3 (ktic_{it} – l_{it}) + \beta_4 N_i (ktic_{it} – l_{it}) + \beta_5 (lc_{it} – l_{it}) + \beta_6 N_i (lc_{it} – l_{it}) + \beta_7 l_{it} + \beta_8 N_i + \varepsilon_{it} \qquad (3)$$

In this case, N represents a variable which takes the value 2 if the firm does innovation in both EAI surveys (2001-2003 and 2004-2006), 1 if the firm implement innovations in only one period and zero if it does no innovation, and ε is the error term of the model. In equation (3), the coefficients may be interpreted as elasticities.

The objective of the empirical section is to test two main hypotheses: i) greater ICT investment is associated to greater productivity at firm level, and ii) ICT investment implies an employed personnel reduction or a reduction of non-qualified workers. To test the first hypothesis, equation (3) is estimated in first differences. In order to evaluate the second hypothesis, the following equation is estimated:

$$l_{it} – l_{it-1} = \alpha + \beta_1 \Delta ktic_{it} + \beta_2 \Delta k_{it} \qquad (4)$$

Equation (4) estimates effects of capital and ICT investments on the variation of employment. Thus, the sign of the estimated coefficient will suggest the complementarity or substitution hypothesis between capital and workers. We also estimate equation (5) to find the effects of investment in the unskilled worker variations and to identify if there are significant differences between the effect on total workers and unskilled workers (lnc_{it}).

$$lnc_{it} – lnc_{it-1} = \alpha + \beta_1 \Delta ktic_{it} + \beta_2 \Delta k_{it} \qquad (5)$$

The data used come from the EAE 2003-2007 and from the EAI 2001-2003 and 2004-2006. We constructed a panel data formed by 738 manufacturing firms which responded at least three EAE between 2003 and 2007 and EAI between 2001-2003 and 2004-2006.

The EAE collects data at firm level concerning gross value of production, value added, workers, intermediate consumption, fixed capital, gross fixed capital formation, industrial sector (4-digit ISIC Rev. 3), among others[2]. The EAE is a stratified sampling survey, where some of the frame units are mandatory (forced stratum) and a random sample is designed for the other units.

The Innovation Survey was divided in two main parts. The first part collects information concerning firms' characteristics, such as type of activity, juridical nature, capital source, number and qualification of employees and sales, among others. The second part collects information related to innovation activities, identifying type of activity and its purpose, resources involved to perform them, their financing source, results obtained, factors that hinder innovation and links with other agents of the National System of Innovation, among other factors. The firm sample includes firms with 5 or more workers. The data on ICT capital, capital source and exports were obtained from the Annual Survey 2003-2007, while the data on product and process innovation were obtained from the Annual Survey 2001-2003 and 2004-2006.

4. Main innovation patterns

The Uruguayan economy has been historically based on livestock production, although in recent years agriculture and services such as tourism, financial services and software, have gained more relevance. The breeding of bovine and ovine livestock are identified as two of the most important activities, and the main exportable products have always been meat, wool and leather. In recent years, there is a trend to increase the participation of agricultural products such as soya, rice and wheat.

Uruguay has shown a strong economic growth since the financial crisis of 2002, and concerning its structure it should be highlighted that the agricultural production is close to 10% of GDP, the manufacturing industry, 16%, trade, restaurants and hotels, 14%, and services 50%, with special mention of real estate and business activities which includes software with 15% and financial services representing 6% of GDP. The growth rate of Uruguay was close to 6% in the period of five years considered in this work, and manufacturing GDP growth was even higher. Thus, its GDP proportion increased from 13.6% in 2003 to 15.2% in 2007. It should be emphasized that this increase follows a strong regional and domestic crisis whose climax occurred in 2002.

[2] See Table A.1 in the appendix for a description of the variables.

In the study undertaken by Bianchi and Gras (2006), using multivariate analysis techniques for analyzing the Survey on Innovation Activities 2001-2003, the innovating process was typified through firm internal capabilities, relationships kept by the firm with the environment in order to develop innovation activities (with agents of the National System of Innovation or others) and innovation experience. This work showed, according to the cognitive base sustained by innovation, that there are three types of firms: those which are less or not innovating (75% of firms considered), those that are based on the incorporation of exogenous knowledge (14%), and those which develop the innovation process by themselves (4.7%).

In the Survey on Innovation Activities, specifically concerning obstacles for innovation, we find that firms responded in the highest proportion to the “small market size” option. The second option was “difficult access to financing”, and in the third place, “macroeconomic instability”. With regard to results of innovating firms in relation to the question about the importance of economic impacts of innovation in a scale from 1 to 4 (being 1 high and 4 not relevant), the response with the highest importance percentage was the option “it maintain firm market share”. The second option was “it improves product quality”, and in the third place, the option “it increase productive capacity”. Additionally, the overall Uruguayan situation is characterized by the following characteristics: i) increasingly demanding customers; ii) pressure on the efficiency to reduce costs and adapt the supply to its particular features; iii) technological progress which generates changes in economic relations; iv) strong competition in international markets; v) certain “aversion to risk” which figures as a negative behavior concerning innovation activities of manufacturing firms. This idea comes from the analysis of section G of EAI, which details some possible obstacles when it comes to developing innovation activities.

The following two tables, with data from the EAE 2006 and 2007, refer to the proportion of firms using ICT and those having Internet and what they use it for. We observe that a very high percentage of firms have computers, use the Internet and have presence in the Web (see Table IX.1 and IX.2). This is so, because the sample is composed by manufacturing firms with more than 50 employees (forced inclusion stratum). The random firms were not a study subject in EAE 2006, so if we considered them, the results would not have been comparable.

Table IX.1

Uruguay: proportion of firms using ICT

(Percentages)

Variable / Year	2006	2007
Proportion of firm with computers	94.7	96.8
Proportion of firms using the Internet	95.1	98.0
Proportion of firms with presence in the Web	68.6	70.3

Source: Author’s own elaboration based on EAE 2006 and 2007.

Table IX.2
Uruguay: ICT use in firms
(Percentages)

Internet Use	2006	2007
Sending or receiving e-Mail	99.3	99.5
Internet banking or access to other financial services	85.1	86.0
Interacting with general government organizations	66.7	67.4
Providing customer service	65.6	64.4
Delivering products online	18.3	18.7
Publicity and marketing	46.2	44.8
Virtual meetings and forums	22.0	22.1
Decision-taking support and/or definition of business operations	42.3	45.1
Getting information about goods and services	90.4	91.8
Getting information from general government organizations	89.0	87.9
Other information search or research activities	70.9	70.9
Receiving orders via Internet	58.0	58.1
Making orders via Internet	59.0	60.0

Source: Author's own elaboration based on EAE 2006 and 2007.

In relation to innovation capabilities of the firms and their effort in this matter, Table IX.3 presents the percentage of firms that innovated by size. As expected, the percentage of firms which innovated increases with the number of personnel employed, in all years. Also, the innovation reduction is evident from one period to another in all segments, even in those firms with more than 200 workers. The possible explanation lies in the fact that the period 2001-2003 included the crisis which affected the Uruguayan economy in 2002. In spite of this situation, manufacturing firms had to make innovations in nearly all areas in order to remain operative. During the crisis, the exchange rate doubled, therefore the external market seemed more attractive to Uruguayan industry. Thus, in 2002 and 2003 many firms were obliged to introduce changes in order to readjust their manufacturing production, remain operative and make their products competitive at both the domestic and international levels. We do not mean that the crisis stimulated innovation, but a certain need was created for firms to innovate so that their products could remain in the market. This competitiveness is based on the ability to produce innovating products and processes, where knowledge and innovation contribute to improve productivity. Precisely for this reason, the percentage of innovating manufacturing firms was lower in the period 2004-2006, because most firms had made innovations in the precedent period, and three years is a relatively short time for local firms to make new innovations.

Similarly, firms with mostly foreign capital are on average more innovative than those whose capital is mostly national. Although both groups showed a reduction of innovation activities in 2004-2006, the difference in favor of foreign firms remains (see Table IX.4). According to the data, we also observed a positive relationship between capital source, size and exports with innovation activity. Indeed, firms with foreign source capital are larger, have the highest exports propensity and a higher innovation rate. Table IX.4 also shows how firms with foreign capital innovated more than those with national capital.

Table IX.3
Uruguay: percentage of innovating firms by size
(Percentages)

Size	Did not innovate	Innovated in 2003	Innovated in 2006	Innovated in both periods
Less than 49 workers	0.36	0.50	0.44	0.30
Between 50 and 99 workers	0.28	0.53	0.55	0.36
Between 100 and 199 workers	0.15	0.72	0.67	0.54
Over 200 workers	0.11	0.82	0.71	0.64

Source: Author's own elaboration based on EAE and EIA, several years.

Table IX.4
Uruguay: percentage of innovating firms by export range and ownership
(Percentages)

Exports (% of sales)	Did not innovate	Innovated in 2003	Innovated in 2006	Innovated in both periods
Exports less than 10%	0.29	0.55	0.56	0.39
Exports between 10% and 50%	0.19	0.70	0.58	0.47
Exports over 50%	0.17	0.70	0.63	0.50
Mostly foreign capital	0.08	0.76	0.76	0.61
Mostly national capital	0.27	0.59	0.54	0.40

Source: Author's own elaboration based on EAE and EIA, several years.

5. Econometric results

This section displays the econometric results by using an unbalanced panel database of 738 firms in 5 years.[3] The dependent variable used is a proxy of productivity (value added per worker), and it has a positive correlation with all interaction factors and terms except one, the interaction between innovation and the proxy of human capital (see Table A.3 in the Appendix). Besides productive factors specified in the model, there are other variables which may explain productivity and productivity differences among firms, like administrative skills, firm culture or ability to obtain intangible resources. The panel structure of the data allows correcting this unobservable heterogeneity when considering the presence of firm specific effects. If these effects are correlated with explanatory variables, fixed effects (FE) methodology must be used; instead, if they are not, random effects (RE) methodology is more accurate.

[3] See table A.2 and A.3 in the Appendix to see variables definitions and Pearson correlation matrix. Additionally, Table A.4 presents a statistical description of variables.

The econometric estimation is implemented by using generalized least squares, because ordinary least squares would be inefficient. We also estimate by weighted least squares for panel data (GWLS), which estimates weighting factors based on the estimations of specific error variances for the respective sample units. This proceeding is an iterative process, and in each round residuals are recalculated using estimated parameters, obtaining a new set of estimators of the specific error variances for each unit, and from there a new set of weighting factors is derived. Overall, the empirical model is estimated by FE, RE and GWLS. See Table IX.5 for GWLS estimation and Tables A.5 and A.6 in the Appendix for fixed and random effects.

The estimation by GWLS shows that all the factors and interactions affected the value added worker. Indeed, ICT capital and innovation interaction with all other production inputs are significant. Nevertheless, in the case of the interaction with ICT capital, the coefficient was negative. With regard to innovation, the model identified that innovation by itself has a negative effect on productivity, although this effect becomes positive when we consider the joint effect with investment both in capital and ICT. One of the reasons that may explains this is the reduced sample and that many firms declared to have implemented innovations when maybe it was not so. The estimation of production functions per worker in first differences shows that capital per worker, ICT capital per worker and employees had positive effects on output growth per worker. Also, innovation was not relevant by itself and had a negative effect on productivity growth when considered together with capital and human capital (see Table IX.6). Jointly, these variables generate an increase in firms' productivity, but they do not increase its growth.

Table IX.5

Estimation Results for the Production Function

Variables	*Coefficient (GWLS) (t-test)*
Constant	10.645 (73.12) ***
k-l	0.152 (14.88) ***
kICT-l	0.030 (3.79) ***
lc-l	0.212 (15.99)***
l	0.038 (3.73)***
N(k-l)	0.118 (11.76)***
N(kict-l)	0.015 (2.21)***
N(lc-l)	-0.064 (-5.307)***
N	-1.510 (-10.69)***
Obs.	1 004
Firms	397
F (8.995)	490.33
Adjusted R-square	0.796

Source: Author's own elaboration.
*Note: * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table IX.6

Estimation results for the production function in differences

Variables	*Coefficient (GWLS) (t-test)*
Constant	0.093 (8.410)***
dk-l	0.035 (2.278)**
dkICT-l	0.030 (3.404)***
dlc-l	0.032 (1.503)
dl	-0.939 (-19.98)***
dN(k-l)	-0.044 (-2.562)**
dN(kict-l)	-0.009 (-1.523)
N(lc-l)	-0.037 (-2.060)**
N	-0.006 (-0.6561)
Obs.	548
Firms	266
F (8.539)	60.54
Adjusted R-square	0.47

Source: Author's own elaboration.
*Note: * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

In order to test the hypothesis that ICT investments affect the employment level negatively, we estimate equation (4). The results suggest that the increase in ICT capital investment has a positive effect in employment growth, in the same way as the increase in non-ICT capital. For the effects on unskilled workers, we estimate equation (5). The evidence shows that non-ICT capital investment has a higher effect than ICT capital, although both have positive effects on labor demand. These results support the ICT complementarity hypothesis, in the sense that they act as general purpose technologies that stimulate the incorporation of new workers to the firm.

Table IX.7

Estimation results for employment growth

Variables	*Coefficient (t-test)*
Constant	0.065 (77.42)***
dk	0.013 (7.347)***
dkTIC	0.010 (8.322)***
F (2.712)	1 012.2
Adjusted R-square	0.73

Source: Author's own elaboration.
*Note: * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

Table IX.8
Estimation results for employment growth of unskilled workers

Variables	*Coefficient (t-test)*
Constant	0.064 (32.09)***
dk	0.015 (5.17)***
dkTIC	0.0108 (9.07)***
Adjusted R-square	0.18
F (2.712)	82.68

Source: Author's own elaboration.
*Note: * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*

6. Concluding remarks

This study analyzes the impact of ICT and innovation on productivity in a sample of Uruguayan manufacturing firms. This represents a first attempt to measure the effect of ICT and innovation investment both on productivity and its growth, and on the demand for skilled and unskilled workers. The econometric estimations show that an increase of ICT capital produces an increase in productivity when we consider the isolated effect of this variable. The opposite happens with innovation, which by itself does not have the expected effects on productivity. Indeed, results show that innovation has a negative effect by itself, but this is reverted when it interacts with capital or ICT capital investments. With regard to the effect on productivity growth, ICT investment does have a positive effect, in the same way as the other factors, except human capital. Again, innovation did not have a positive effect. On the other hand, increases in ICT capital investments have a positive impact on labor demand variations. This effect is also maintained on the demand for unskilled employees, although with a somewhat lower coefficient than for other capital.

In Uruguay, there is no research on the effects of ICT or innovation on productivity at firm level. The main obstacle is that there are no surveys exclusively on ICT; questions are included in only one chapter of the Structural Survey of Economic Activity since 2005. Moreover, in the Surveys on Innovation Activities there are no ICT questions either. In our empirical exercise, we relied on a reduced number of firms having detailed data for several periods so as to make a panel analysis. This limitation is expected to disappear when the quantity and quality of data are improved through successive Surveys on Innovation Activities and Structural Surveys of Economic Activity. Another limitation is that the empirical model does not disentangle among product, process or organizational innovations, nor does it consider variables like organization culture or new practices of labor organization and its complementarities with ICT.

Additionally, it also seems necessary to study the sampling method in the Innovation Surveys, both for the manufacturing industry and for services. We perceive that employed personnel are not adequate for stratifying. It should be discussed if other variables, like sales, investments or activity class are more adequate for this purpose. There continue to be many doubts on this matter. Other important gaps in the survey are related to the fact that there is no information about how much the firms invest in ICT, and if they actually give it the right use. We propose to work in a base questionnaire, with a shared purpose, shared, research unit, activity classification and shared definitions. In addition, the questionnaire must last several years in order to have a consistent and comparable series.

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8. Appendix

Table A.1
Variables Definitions

Variable	Definition
Gross fixed capital formation	Investments in buildings, machinery or facilities of any kind, which in collaboration with other factors, are intended for the production of consumer goods. It is captured in current values by the Structural Survey of Economic Activity and transformed to constant values by using the Price Index of National Products (IPPN – Índice de Precios de Productos Nacionales) elaborated by INE.
Gross fixed capital formation in ICT	Investments in informatics and telecommunications. These technologies provide innovation to the firm, and tools for its process and communication channels. It is captured in standard values by the Structural Survey of Economic Activity and carried to constant values by using the Import Price Index of Capital Assets (Índice de Precios de Importación de Bienes de Capital), elaborated by the Central Bank of Uruguay.
Human capital	Set of human resources owned by a firm or economic institution. We speak of improvement in human capital when the degree of skill, know-how or education background of the employees increases.
Personnel employed	Total number of employees in the firm.
Professionals and technicians	Number of employees with university degree or who have a major in the task they develop.
Capital source	Foreign capital participation in the firm's total capital. The Annual Survey of Economic Activity establishes three categories: no share, less than 50% of the capital, 50% or more.
Value added	Difference between production value of goods and services produced and the intermediate consumption used in their production, carried to constant prices by using the corresponding Pasche Price Index of the Survey of the Physical Volume Index for each 4-digit activity class of ISIC Rev.3.
Product innovation	Introduction of technological or other changes in a product. Innovation is produced when the characteristics of a product change.
Process innovation	Introduction of significant changes in production technology. It also happens when there are changes in management system or organizational methods, process reengineering, strategic planning, quality control, etc.
Organizational innovation	Introduction of changes in organizational and management aspects of the firm; changes in the organization and administration of productive process, incorporation of significantly modified organizational structures and implementation of new or substantially modified strategic guidelines.

Source: Author's own elaboration.

Table A.2
Variables used in econometric analysis

Variable	Definition
y-l	Logarithm of value added by employee in constant pesos.
l	Logarithm of number of employees.
kict-l	Logarithm of ICT capital per employee in constant pesos.
k-l	Logarithm of capital per employee in constant pesos.
lc-l	Logarithm of the proportion of professionals and technicians per employee.
N	Variable which takes the value zero if the firm declares to have made no innovation in any of the two innovation surveys, 1 if it introduced any innovation in only one of the surveys and 2 if it implemented it in both surveys.

Source: Author's own elaboration based on EAE and EIA, several years.

Table A.3
Pearson correlations

y-l	l	kict-l	k-l	lc-l	N(kict-l)	N(k-l)	N(lc-l)	N	
1	0.26	0.26	0.52	0.10	0.44	0.40	-0.29	0.34	y-l
	1	-0.03	0.32	-0.48	0.44	0.41	-0.52	0.38	l
		1	0.29	0.11	0.35	0.14	-0.04	0.10	kict-l
			1	-0.02	0.38	0.41	-0.29	0.29	k-l
				1	0.00	-0.03	0.46	-0.03	lc-l
					1	0.97	-0.85	0.97	N(kict-l)
						1	-0.87	0.99	N(k-l)
							1	-0.87	N(lc-l)
								1	N

Source: Author's own elaboration based on EAE and EIA, several years.

Table A.4
Basic statistics

Variable	Mean	Median	Min.	Max.	Standard Dev.
l	4.01	3.98	0.69	8.50	1.16
y-l	12.45	12.42	5.94	18.08	1.06
kTIC -l	8.78	8.93	-1.41	19.38	1.99
k-l	12.15	12.30	-4.34	16.62	1.61
Lc-l	-2.88	-2.80	-7.02	0.01	1.02
N(kTIC-l)	6.17	0.00	-1.41	27.49	7.30
N(k-l)	11.04	11.96	-4.34	33.06	9.58
N(lc-l)	-2.45	-2.27	-14.04	0.00	2.52
N	0.89	1.00	0.00	2.00	0.73

Source: Author's own elaboration based on EAE and EIA, several years.

Table A.5
Estimation results of the production function

Variable	Fixed effects	Random effects	GWLS
Constant	15.408 (23.01)***	10.95 (22.70)***	10.646 (73.12)***
k-l	0.038 (0.61)	0.167 (4.747)***	0.152 (14.88)***
kTIC-l	-0.001 (-0.0775)	0.006 (0.3353)	0.030 (3.793)***
lc-l	-0.010 (-0.15)	0.100 (1.879)*	0.212 (15.99)***
l	-0.68 (-9.73)***	-0.141 (-3.626)***	0.038 (3.734)***
Innova(k-l)	-0.010 (-0.2293)	0.071 (2.302)**	0.118 (11.76)***
Innova (ktic-l)	0.002 (0.1587)	0.009 (0.595)	0.015 (2.211)**
Innova (lc-l)	-0.017 (-0.4081)	-0.058 (-1.626)	-0.064 (-5.307)***
Innova		-0.738 (-1.805)*	-1.510 (-10.69)***

Source: Author's own elaboration.
*Note: * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*
Fixed effects model
Contrast of different intercepts per groups – Null Hypothesis: the groups have a common intercept. Contrast statistics: F(396.6) = 11.2364 with p value = P(F(396,6) > 11.2364) = 1.55586e-145.
Random effects model
- Breusch-Pagan contrast - Null Hypothesis: Variance of error specific to unit = 0. Asymptotic Contrast Statistics: Chi-square (1) = 490.194 with p value = 1.29312e-108
- Hausman Contrast – Null Hypothesis: the estimators of GLS are consistent. Asymptotic Contrast Statistics: Chi-square (7) = 122.045 with p value = 2.87296e-023

Table A.6
Estimations results: fixed effects, random effects and weighted least squares

Variable	Fixed effects	Random effects	GWLS
Constant	0.084 (4.12)***	0.120 (2.85)***	0.093 (8.41)***
dk-l	0.088 (1.12)	0.037 (0.718)	0.035 (2.27)**
dkTIC-l	0.024 (0.83)	0.026 (1.17)	0.030 (3.40)***
dlc-l	0.033 (0.38)	0.025 (0.37)	0.032 (1.50)
dl	-0.911 (-8.06)***	-0.879 (-10.02)***	-0.939 (-19.98)***
dN(k-l)	-0.096 (-0.11)	-0.058 (-1.29)	-0.044 (-2.56)**
dN(ktic-l)	-0.004 (-0.19)	-0.009 (-0.55)	-0.009 (-1.52)
dN(lc-l)	-0.054 (-0.99)	-0.037 (-0.84)	-0.037 (-2.06)**
N		-0.026 (-0.86)	-0.006 (-0.65)

Source: Author's own elaboration.
*Note: * Significant at 10%; ** Significant at 5%, *** Significant at 1%.*
Fixed effects model
Contrast of different intercepts per groups – Null Hypothesis: groups have a common intercept. Contrast statistics: F(265.275) = 1.1066 with p value = P(F(265.275) > 1.1066) = 0.202673.
Random effects model
- Breusch-Pagan contrast - Null Hypothesis: Variance of error specific to unit = 0. Asymptotic Contrast Statistics: Chi-square (1) = 7.23672 with p value = 0.00714274.
- Hausman Constrast – Null Hypothesis: the estimators of GLS are consistent
Asymptotic Contrast Statistics: Chi-square (7) = 2.72639 with p value = 0.909108.

V. ICT, organizational change and firm performance: evidence from Argentina

Elisa Calza
Sebastián Rovira

1. Introduction

Information and Communication Technologies (ICT) define a wide range of material as well as non-material elements. It consists of computing equipments (PC, micro processors and other hardware components), software, communication media (TV, landline and mobile phones) and multi-media elements, interactive applications and related services. In the past few decades, ICT have been diffused rapidly around the world, due in part to impressive technological progress in component design and production methods —especially for microprocessors— which has contributed to a shrinkage in ICT prices. Apart from the broad and rapid diffusion of ICT, one of the most striking features of ICT is the wide scope of applications and of co-inventions made possible by its use. These properties that distinguish ICT from other capital goods have motivated scholars to designate ICT as a "General Purpose Technology" (GPT).[1] GPTs open up possibilities for the creation of new industries, but they can also stimulate new applications of already existing technologies and revitalize existing sectors (Dosi, 1982; Freeman and Perez, 1988; David and Wright, 1999; Aghion, 2002). In this sense, it is easy to grasp the GPT nature of ICT: the application of ICT has allowed the emergence of new business sectors, such as Internet providers, or the development of network communication equipments, and it has changed the protocol and scope of activities of sectors such as finance, banking, and consulting, among other services.

Given the magnitude and rising importance of the phenomenon, scholars of economic growth and ICT have started to address the effects originated by the increased use of ICT in firms, particularly regarding the relationship between ICT and productivity. Investigating the impact of ICT has proven to be a tough task, considering the nature of GPT. Indeed, since GPT facilitate complementary innovations, it is reasonable to suppose that contributions of ICT to productivity may go through multiple channels (*e.g.* organizational changes, quality of human capital, production methods, among others)

1 ICT are compared to other important inventions that in the past had a fundamental role in inducing major changes in the system of production and institutional settings, such as electricity and the steam engine (David, 1990; Helpman, 1998; Rosenberg and Trajtenberg, 2001).

and that some fraction of productivity boosted by ICT might be strengthened by other transmission mechanisms. This means that it is important to distinguish between “direct” and “indirect” effects of ICT over productivity, even if this makes it particularly difficult to adequately measure the role of ICT by quantitative analysis.

Furthermore, the impact of GPT might take place also through a series of secondary innovations; this means that GPT can be considered also as ‘enabling technologies’, since they might require further innovations in their application to fully unfold their potentialities (Bresnahan and Trajtenberg, 1995). GTP need to be accompanied by secondary and side innovations, which leads to the concept of continuous co-invention across new and acquired technology, and of complementarity. In fact, it seems plausible that ICT implementation is not sufficient to cause positive productivity effects: ICT may require skilled labor to be adequately employed, and some firms may be able to use ICT better and more productively than others due to their human capital, experience and organization. In the same way, organizational improvements may also be needed to fully take advantage of ICT potentialities, since ICT enables information to flow and circulate more quickly. This simultaneously allows and requires firm structures to become more flexible. These features are expressed by the concept of complementarity.

This paper aims at analyzing how and to what extend ICT may affect firms’ productivity in the Argentinean manufacturing sector. The underlying channels for this effect are related to improving firms’ internal and external information flows, allowing them to obtain a better and faster exchange of information not only among its own members, but also from suppliers, costumers and third parties. Moreover, ICT use may induce the modification of professional requirements, fostering employment of more qualified human capital and enabling changes at organizational level (even made possible by the same improvement of human capital), which in turn end up positively affecting firm productivity. In this context, this study also seeks to shade light on the existence of complementarities in Argentinean manufacturing firms. In particular, it analyses the role of human capital and organizational changes as transmission channels that reinforce the direct impact of ICT, by affecting firms’ productivity in an indirect way. In particular, a special attention is dedicated to organizational changes in strengthening ICT impact.

Since most of the literature is based on the experiences of developed countries, this is one of the few studies that analyzes ICT, firm performance and organizational change in a developing country. The empirical analysis confirms the existence of a positive relationship between ICT and firm productivity in Argentinean manufacturing firms. Additionally, results seem to support the complementarity hypothesis between ICT, human capital and organizational change.

The study is structured as follows. Next section presents a brief literature review, and section 3 provides a description of data used in the empirical analysis, presenting an overall picture of Argentinean manufacturing sector. Then, section 4 describes the theoretical model with its main hypotheses and variables used, while section 5 discusses the econometric analysis. A final section includes closing remarks and follow-ups.

2. Literature review

This section discusses the empirical literature on ICT and firm performance. First, we discuss the literature about how to measure the direct effect of ICT on productivity. Second, we focus on the channels through which ICT investments may affect productivity, distinguishing between “direct” and “indirect” ICT effects. This will lead to the debate over the existence of a complementarity between ICT and other firm dimensions: among these, we pay special attention to organizational changes. Finally, we comment on important methodological issues and theoretical caveats that have been highlighted in the literature.

(a) ICT and productivity: from aggregate to micro level analyses

In last decades, and given the relevance of the phenomenon, several scholars have begun to address the effects originated by the increasing use of ICT, particulary around the issue of ICT, productivity and economic growth. Many studies aimed at analyzing the effect of ICT on productivity, mainly using two types of capital variables: ICT and non-ICT. However, most analyses were performed at the aggregate level (country and industry), and empirical results were ambiguous. In fact, in the 1980s and early 1990s, empirical research generally did not find relevant productivity improvements associated with ICT investments (*e.g.* Strassmann, 1990; Lovemann, 1988; Bender, 1986; Franke, 1987). The inconsistency between the theoretical and empirical analyses regarding ICT impacts was defined as “Productivity Paradox”.

Different rationales were suggested to explain this paradox. First, concerning technical aspects, working with aggregate data raised several methodological issues: (i) use of simple bivariate correlations between aggregate productivity and aggregate ICT capital stock (Lehr- Licthemberg, 1999); (ii) potential negative effect of augmented variety on productivity (Barua *et al*., 1991); and (iii) dynamic effect of ICT investment on productivity gains and its dependence on network externalities and complementary infrastructure (David, 1990). Second, in many cases databases quality was questionable, samples were small and often non-representative and proper deflators were not used. Third, the supposed positive relationship between ICT and productivity was probably more complex to analyze than expected and required a longer time prospective to be properly addressed (Brynjolfsson, 1993). Furthermore, these studies embodied strong assumptions over the existence of a causal relationship between firm performance and ICT investments, which imposed relevant econometric constraints such as, for example, overestimation of coefficients due to endogeneity and heterogeneity problems.

Since the mid-1990s, the availability of microdata related to firm performance and ICT has increased. As a result, firm-level studies allow for including a set of sufficient factors that affect the impact of ICT investments and that cannot be identified through aggregate analyses. In fact, the adoption of ICT and its appliances is highly heterogeneous between countries and industries (Hempell *et al*. 2004; Hollenstein, 2002). Hence, in this context, one of the main advantages of dealing with firm level data is that it allows identifying the differences between sectors in relation to ICT usage, ICT effects, understanding microeconomic behavior related to ICT investment, among others.

Using firm level data, some studies found evidence that ICT is associated with improvements in productivity, intermediate measures and economic growth. For example, Brynjolfsson and Hitt (1996) studied firm productivity using a Cobb-Douglas specification, where they controlled for two types of capital —computers and non-computers— and two types of human capital, ICT users and non-users.[2] Applying iterative seemingly unrelated regressions, these authors found a positive effect of computer investments over productivity. Also Hempell (2002) found significant productivity effects of ICT; moreover, his study entails strong support for the hypothesis that experience gained from past innovations is a specific complement that makes ICT investment more productive, and firms with innovative experience are more likely to make more productive use of ICT by introducing appropriate complementary innovations.

Despite improvements in using firm level data, measuring and assigning a precise magnitude to this relationship is not an easy task; for this reason it is not surprising to find different and in some cases ambiguous results even in the recent literature. For instance, Greenan *et al.* (2001) found that estimations are significant and with the expected sign using cross section analyses, but significance disappears in time series analyses. Similarly, Van Leeuwen and Van der Wiel (2003) proposed an empirical approach based on an enhanced production function model, but after accounting for ICT spillovers, the relatively high estimated elasticities of ICT capital at the firm level are substantially reduced.

2 Following a similar approach, other studies that found evidence of a positive relationship between computer capital and productivity using firm level data are Oliner and Sichel (1994), Lichtenberg (1995), Sichel (1997), Licht and Moch (1999), Lehr- Licthemberg (1999), Greenan and Mairesse (2000), Zwick (2003), Chowdhury (2006). and Badescu and Garcés-Ayerbe (2009). Chowdhury (2006) is one of the few studies that study the ICT effect on productivity in developing countries, using data from Kenya and Tanzania.

(b) Channels of ICT effects on firm productivity

Despite the fact that ICT direct contribution to firm performance may be relevant, its impact may be reinforced by the existence of simultaneous factors which complement the ICT effect; these factors are human capital, innovation and organizational change. Beyond the existence of a "direct" effect of ICT on firm performance, the relationship between ICT and the demand of skilled labor, innovation activities and organizational changes have been largely considered in the literature, referring to possible effects on productivity as "filtered" by these transmission mechanisms, thus, as ICT "indirect effect".

As far as human capital is concerned, quantitative research has already established that there is a positive correlation between ICT and skill at employee, firm and industry level. In fact, firms do not simply plug in computers or telecommunications equipment and achieve service quality or efficiency gains; instead, firms go through an often lengthy and difficult process of co-invention, where ICT sellers invent technologies and ICT users must co-invent applications to exploit these technologies. This is what is called skill-biased technical change (SBTC): technical progress that shifts demand toward more highly skilled workers relative to less skilled. In the specific case of ICT, it implies that the increase of demand for higher skilled labor induced by ICT investments would positively affect firm performance. This idea is argued in Roach (1991), Berndt *et al*. (1992) and Stiroh (1998). Also Black and Lynch (2001), using a Cobb-Douglas specification, found a positive relationship between productivity and several human capital measures. The same results are discussed in Hempell (2005), who found evidence of a positive effect on firm productivity. This suggests that the quality of human capital can be considered a sort of pre-requisite to the positive effect of ICT on productivity.

The literature has also studied other transmission mechanisms, such as innovation and organizational change. Concerning ICT and innovation, Barua *et al.* (1991) argue that ICT investments have a positive effect on productive variety, since investments in telecommunications are likely to positively affect the introduction of new products or processes. In a different approach, Becchetti *et al.* (2003) analyze the determinants of ICT investments, distinguishing among investments in software, hardware and telecommunication, and their impact on productivity (measured as total factor productivity, labor productivity and technical efficiency by using a stochastic frontier approach). The empirical evidence suggests a positive and significant impact of ICT investment on productive efficiency: software investments have the expected sign and have scale effects by increasing the demand for high skilled workers, while telecommunication investments have scope effects by positively affecting the implementation of new processes or products. Additionally, the combination of these two effects increases productive efficiency and utilization capacity, while hardware investments have no significant impact on productivity.

The third channel is organizational change. Many studies have investigated the effect that workplace reorganization and human resource management may have on improving productivity, and an increasing portion of the literature has focused on the impact of ICT-induced organizational change on firm productivity.[3] In a pioneer work, Leavitt and Whisler (1958)[4] predicted in 1958 that ICT use would lead to the demise of middle management and that the number of hierarchy levels in organizations will decrease if, for example, computers are increasingly often used to perform the functions of middle management. Nowadays, the literature reports a variety of forms of organizational change, since ICT use may spur decentralization of authority and more flexible forms of division of labor, such as: changes to authority relationships or decentralization of decision authority; shifts in the task content of clerks', professionals', and managers' work; changes in reward schemes (Milgrom and Roberts, 1990; Brynjolfsson and Mendelson, 1993; Radner, 1993; Davenport, 1994; Davenport and Short, 1990; Hammer, 1990), which tends to reduce coordination costs within and between firms (Drucker, 1988; Malone and Rockart, 1991); iii) redefinition of firm boundaries (Malone *et al.*, 1987; Gurbaxani and Whang, 1991; Clemons and Reddi, 1993), reduction in vertical integration and weak increment in diversification, consistently with theoretical arguments that both internal and external coordination costs may be reduced by ICT (Hitt, 1999).

Among the benefits that the introduction of ICT may induce, the reduction of the cost of information and communication is probably the most evident. However, if on one hand ICT investment may considerably reduce transaction and information costs, on the other it may be also related to an increase in costs associated to decentralization, such as a higher risk of information duplication, increased probability of mistakes due to a lower level of control and reduced returns to specialization. Hence, to the extent that the firm internal organization is determined by the economics of information and communication and by the balance between costs and benefits of ICT investments, these technologies may change the firm optimal structure and thus contribute to improve productivity.

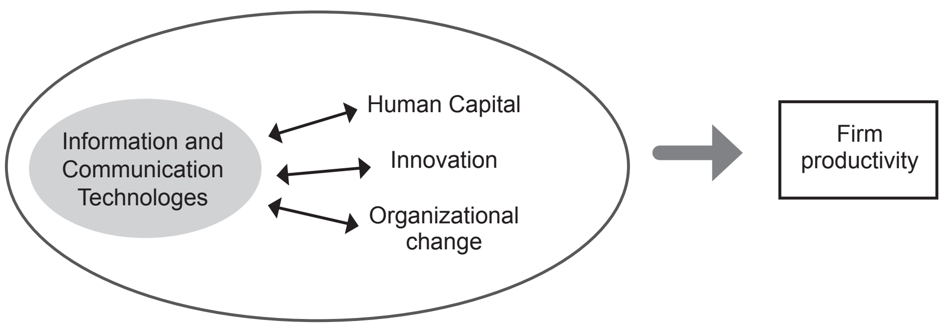
(c) The hypothesis of complementarity

ICT may have both a direct and indirect effect on productivity, "filtered" by improvements in innovation, human capital and organizational change. Nevertheless, ICT impact is supposed to be further strengthened by the existence of mutually reinforcing complementarities among these dimensions. The use of ICT is thought to induce an improvement in employees' skills; in turns, these same improved skills would raise benefits and reduce costs of decentralization and reorganization, facilitating and strengthening

[3] See Eriksson (2003); Huselid (1995); Ichniowski *et al.* (1997).
[4] Quoted by Crowston and Malone (1988, p. 1051).

the impact of organizational change on overall productivity. For example, the use of ICT increases the volume of data analysis and transactions within and across firms, which may lead to modifications in firm organization and call for improvements in analytical and cognitive skills (*e.g.* marketing analysis and quality control data analysis capabilities). When workplace reorganization is introduced or at least favored by enhanced skills, it is defined as skill-biased organizational change (SBOC). Improved skills may not only be the result of ICT investment —such as the definition of skill-biased technical change predicts— but they become a crucial factor in reinforcing the same effect of ICT investments on other activities, such as innovation and organizational change, with the effect of further strengthening the scope of ICT impact on firm performance (see Figure X.2). In sum, complementarity implies that higher skills and organizational changes may be the only way to make ICT investment truly effective in terms of productivity gains. According to this approach, it seems plausible that the implementation of new technologies by itself would not be sufficient to induce —and account for— positive productivity effects.

Figure X.1
Hypothesis of complementarity



Source: Authors' own elaboration.

While early studies focused on analyzing direct causal links between ICT and labor demand, recent literature on ICT, organizational change and firm performance has shown an increasing interest in investigating the hypothesis that ICT may serve primarily as 'enabling technologies' that require additional complementary innovation efforts to fully unfold their productivity potentials. Most of these studies focus on complementarities between human capital and organizational change, finding empirical evidence that ICT and workplace reorganization jointly have positive effects on productivity. Bresnahan *et al.* (2002) was one of pioneering studies to tackle this issue. The authors investigated the hypothesis that the combination of ICT, workplace re-organization and innovation in new products and services may constitute a significant skill-biased technical change affecting labor demand in the United States. Indeed, the empirical results suggest the existence of complementarities among these three dimensions in both labor factor demand and productivity. Moreover, ICT investment is found to be a determinant of the level of human capital, since firms that adopt one or more ICT tend to use more skilled labor, which turns out to affect productivity more effectively. Since ICT investment, work organization and human capital are found to positively predict firm productivity, the effects of ICT on labor demand are greater when ICT is combined with the particular organizational investments, highlighting the importance of ICT-enabled organizational change in boosting productivity.

Brynjolfsson and Hitt (2003) considered the implications of dynamic complementarities, suggesting that a larger time lap may be required to observe a positive impact of ICT on productivity. Also, many studies found complementarities at least between some of the three elements (mainly between ICT and human capital) (Caroli and Van Reenen, 2001; Black and Lynch, 2001; Gargallo-Castel and Galve-Górriz, 2007a). However, despite improvements in data availability and methodologies used, empirical results are far from being conclusive and hypotheses about the real role of ICT in affecting firm productivity are still controversial.[5]

In a different empirical approach, Arvanitis (2005) analyzes the relationship between ICT, productivity and organizational change using unconventional proxies for ICT (percentage of employees working with Internet and Intranet) and organizational change (percentage of team work, employees' rotation and duties assignment). The simplest version of his model showed that ICT-related variables are significant and positively associated with productivity. Furthermore, there is evidence on the existence of complementarities between ICT, human capital and organizational change. This work served as base for the study of Arvanitis and Loukis (2009), where they used different measures for ICT investment, human capital and organizational change to verify the hypothesis of complementarity in Greek and Swiss firms. They found that productivity in general is positively affected by ICT and human capital, but there is no strong empirical support for the complementarity hypothesis. Also Giuri *et al.* (2008) examine complementarities between ICT, skills and organizational change in Small and Medium Size Enterprises (SMEs). They do not find evidence of complementarity between ICT and skills, nor between ICT and organization; instead, they find evidence of complementarity between organizational changes and skilled labor, arguing that organizational change may be effective in affecting skilled labor productivity. Their results suggest that hypothesis of full complementarity among ICT, human capital, and organizational change may not apply to SMEs, where organizational change might even yield negative effects on the complementarity between ICT and human capital.

[5] See Bresnahan and Trajtenberg (1995); Milgrom and Roberts (1990, 1995); Brynjolfsson and Hitt (2000); Bertscheck and Kaiser (2003) and Becchetti *et al.* (2003).

(d) Issues and shortcomings

The findings reported in the literature show how the complex nature of ICT and their interactions with firm performance make it difficult to implement an adequate empirical analysis. Moreover, micro-level studies confirm that firm conditions matter and that it is crucial to investigate firm specific circumstances in which ICT are used in order to asses its impact. Thus, some caveats have to be kept in mind. First, in most of the studies there is a simultaneity problem: they assume a unidirectional relationship between productivity and workplace reorganization but ignore a potential reverse causality. Selection bias problems need also to be considered (Bertscheck and Kaiser, 2003). In fact, it is likely that firms with organizational changes do not only differ from other firms with respect to their organizational form, but also in other elements such as skill mix, investment strategies or unobservable characteristics, which may be important in explaining firm performance. Related to firm unobservable characteristics, there may be an issue of strategic complementarity. Indeed, Milgrom and Roberts (1990) argue that it might be too restrictive to assume that firms produce according to the same production function independent of the way workplaces are organized. Also, they claim that considering the effect of workplace reorganization to simply change the constant term in a production function context neglects that this may also modify firms' strategies with respect to skill mix and investment, and that these changes may have impacts on firm productivity.

Another important methodological issue is related to the quality of data. Cross-section data do not allow accounting for lagged effects of ICT on productivity, and "*the effects of ICT are substantially larger when measured over longer time periods"* and if productivity growth is considered rather than productivity levels (Brynjolfsson and Hitt, 2000, p. 33). Since there are different adjustment costs and adjustment timing across complementary dimensions, effects on productivity are likely to occur only in a dynamic context. The adjustment time is firm-specific and therefore we should expect cross-sectional differences in the adoption of complements across firms. Another potential drawback is that many studies assume a Cobb-Douglas production technology. Using a Cobb-Douglas specification implies an elasticity of substitution of unity between input factors, and it does not take into account the possibility that organizational change might vary the elasticity of substitution between input factors. A popular alternative is to use the Translog approach, but would also imply a potential problem of collinearity between explanatory variables.

Related to the hypothesis that firm characteristics are important in determining the sensitivity and even the existence of a relationship between ICT and productivity, Giuri *et al.* (2008) argue that this relation is much weaker —even inexisten— in the case of SMEs. They report three main reasons.First, many available technological solutions have been developed for the needs of large firms and do not account specific organizational characteristics of smaller firms (Levy and Powell, 2000). Second, SMEs typically adopt more flexible and simpler organizational structures than large firms: higher levels of organizational efficiency in these firms can be achieved by small organizational changes and a more intensive use of skilled labor without necessarily adopting complex ICT solutions. Third, several SMEs then invest in basic ICT infrastructure such as computers and Internet connection that require some skill upgrading but do not require significant organizational changes. Indeed, given the simplicity of SMEs' organizational structures, an intensive ICT use associated with skilled workers and new organizational practices might unnecessarily overburden the educated labor.

3. Data description

This study is based on the National Survey on Innovation and Technological Behaviour (*Encuesta Nacional sobre Innovación y Conducta Tecnológica*, ENIT), collected by the National Statistics and Censuses Institute of Argentina (INDEC) in 2005. The sample includes 1,670 manufacturing firms with 5 workers or more, and is representative of the whole manufacturing industry. A first section of the survey aims to collect general information about firm characteristics and activities, such as sector, employees and their level of education, sales and exports, among others. Firms are classified according to sector technological intensity: low, medium-low, medium-high and high.[6] According to this classification, almost 50% of firms are characterized by having low technological intensity; of the remaining 50%, most firms (around 20%) are almost equally distributed between medium-low and medium-high technological intensity sectors, while firms in high technological intensity sector represent 9% of the sample (Table X.1). Firms are also categorized according to number of employees in four groups: small (less than 50 employees), medium-small (between 51 and 100), medium (between 101 and 200), medium-large (between 201 and 500) and large (more than 500) (see Table X.2). Small firms represent almost 1/3 of the whole sample; medium firms represent the second largest group with 24%, and medium-small and medium-large firms follow with 18% and almost 16%, respectively. Large firms are a relative minority, since they represent only 10% of the sample.

Table X.1
Firm distribution by technological intensity
(*Number and percentages*)

Sectors	Low	Medium-low	Medium-high	High	Total
Number of firms	824	331	368	147	1 670
Percentages	49.3%	19.8%	22.0%	8.8%	100%

Source: Authors' elaboration on the basis of ENIT 2005.

6 See Table A.1 in Appendix for the description of different sector categories.

Table X.2
Firm distribution by firm size
(*Number and percentages*)

Size	Small (50<)	Medium-small (51-100)	Medium (101-200)	Medium-large (202-500)	Large (>501)	Total
Number of firms	523	307	403	263	174	1 670
Percentages	31.3%	18.3%	24.1%	15.7%	10.4%	100%

Source: Authors' elaboration on the basis of ENIT 2005.

In order to have a better idea of the distribution of firms within the sample, Table X.3 displays a matrix crossing firm size and firm technological intensity dimensions. First of all, there is a relative concentration of firms in the first cell, representing "small and with low technological intensity" firms, where the 50% of small and almost 32% of low technological intensity firms are located. Moreover, most of firms distribute along the row of "low technological intensity" (where medium-small, medium and medium-large firms represent 15%, 27% and 16.5% of all firms classified as having low technological intensity, respectively) and the column of "small" (where firms with medium-low and medium-high technological intensity represent 20% and 21% of all small firms, respectively). Firms with high technological intensity represent less than 11% of the total sample and they do not have a large incidence in terms of employment: almost 50% of firms with high technological intensity are small and medium-small firms. The group of "large firms with high technological intensity" constitutes a small group, since almost 60% of large firms concentrate in activities with low technological intensity. Hence, interestingly, large firms are not more likely to have higher technological intensity than smaller firms. This could be explained by the fact that many large firms operate in natural resources processing and primary products.

Table X.4 describes employment distribution by firm groups. Despite the fact that large firms represent only 10% of the sample, they absorb more than 50% of the employed labor force. In fact, firms with up to 500 workers (from small to medium-large) have an average number of employees that represent a value in the middle of the range used to define firm size (thus, the average level of employees approximate the median value), but this does not hold for large firms, whose average number of employees is far above the upper threshold value of 500 workers. Moreover, the data reveal that the Argentinean manufacturing sector present a clear polarization in firm distribution, characterized by few extremely large firms (10%) employing more than 50% of labor force, and a large number of small and medium firms (up to 200 employees) that represent the 75% of the firms but all together do not manage to reach the 25% of total employment (see Table X.4).

Table X.3
Firm size and technological intensity
(Number and percentages)

Tech. Intensity \ Size	Small (50<)		Medium-Small (51-100)		(Medium) 101-200		Medium-Large (201-500)		Large (>500)		Total
Low	263	31.9%	126	15.2%	195	23.6%	136	16.5%	104	12.6%	824
	50.2%		41.0%		48.3%		51.7%		59.7%		
Medium-low	109	32.9%	65	19.6%	86	25.9%	46	13.9%	25	7.5%	**331**
	20.8%		21.1%		21.3%		17.4%		14.3%		
Medium-high	113	30.7%	80	21.7%	93	25.2%	55	14.9%	27	7.3%	**368**
	21.6%		26.0%		23.0%		20.9%		15.5%		
High	38	25.8%	36	24.4%	29	19.7%	26	17.6%	18	12.2%	**147**
	7.2%		11.73%		7.2%		9.8%		10.3%		
Total	523		308		404		264		175		1 670

Source: Authors' elaboration on the basis of ENIT 2005.

Table X.4
Employment distribution by firm size
(Number and percentages)

Size	**Small (50<)**	**Medium-small (51-100)**	**Medium (101-200)**	**Medium-large (202-500)**	**Large (>501)**	**Total**
Employees	12 975	22 416	60 449	84 212	217 202	397 254
Share over total employees (%)	3.2	5.6	15.4	21.2	54.6	100.0
Average employees per firm	24.8	73.0	150.0	320.2	1 248.3	237.8

Source: Authors' elaboration on the basis of ENIT 2005.

Concerning educational levels, 12% of employees have a university degree, while the remaining 88% is almost equally split between workers with vocational and basic education (see Table X.5). The share of professionals employed and of vocational education increases with firm size, reaching the level of 14% and 43%, respectively, in large firms. Thus, data show that large firms tend to employ more people with better qualifications. This suggests two different and complementary interpretations: first, large firms do not need to externalize activities and tend to perform internally all different functions, including those that require higher competencies (*e.g.* design, commercial services, costumer assistance, marketing, among others); second, that larger firms are likely to have more complex organizations, which in turns requires more qualified people and with different specializations.

Table X.5
Education levels by firm size
(*Percentages*)

Educational categories	Average	Small (50<)	Medium-small (51-100)	Medium (101-200)	Medium-large (202-500)	Large (>501)
Professionals	12.3	6.8	9.1	10.8	10.9	13.9
Engineers	5.5	2.8	4.8	5.1	4.4	6.3
Other professionals	6.7	4.0	4.2	5.7	6.4	7.6
Vocational education	41.9	37.8	38.7	40.1	42.3	42.9
Basic education	45.7	55.2	52.1	49.0	46.7	43.1

Source: Authors' elaboration on the basis of ENIT 2005.

The second section of ENIT 2005 is dedicated to innovation activities and corresponding investments. Table X.6 reports firm participation in different innovation activities. Firms' involvement in innovation activities increase monotonically with firm size: the percentage of firm performing innovation activities rise from 39% of small firms to more than 85% in the case of large firms (see Table X.6). The activity that tends to attract the largest participation of firms independently from firm size is Equipment acquisition, followed by Hardware acquisition, Training and Software acquisition. Only 15% of small firms perform R&D internal activities, but this percentage rise monotonically up to 60% for large firms. Moreover, in the case of small firms, Equipment acquisition is the only activity with a higher participation than 20%, while in large firms its participation is 57%.

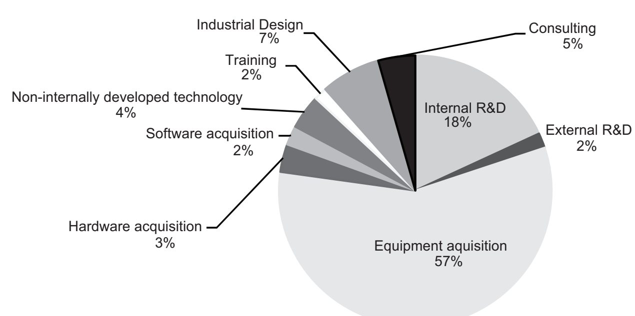
Table X.6
Innovation activities by firm size
(*Percentages*)

Activity / Firm size	Average	Small (50<)	Medium-small (51-100)	Medium (101-200)	Medium-large (202-500)	Large (>501)
Innovating firms (at least 1 of activities listed below)	61.8	38.8	63.5	69.7	77.5	86.7
Internal R&D	31.0	14.9	27.0	34.4	44.8	58.0
External R&D	8.3	3.6	7.8	10.1	9.8	16.6
Equipment acquisition	39.8	23.5	38.4	46.9	51.3	57.4
Hardware acquisition	36.2	19.8	39.0	40.2	47.1	55.1
Software acquisition	25.3	10.1	26.7	28.7	33.8	47.7
Disembodied technology	7.2	3.0	4.8	8.4	11.4	14.9
Training	28.9	12.6	27.3	34.4	43.7	45.9
Industrial design	20.5	10.3	19.8	24.0	27.3	33.9
Consulting	14.9	7.2	12.7	17.8	22.4	24.1
Number of firms	1 670	523	307	403	263	174

Source: Authors' elaboration on the basis of ENIT 2005.

ENIT 2005 presents information on invested amounts in different innovation activities (see Figure X.2). Coherently with previous data, Equipment acquisition plays a leading role: it concentrates almost 60% of total innovation expenditures; Internal R&D follows with 18%, and the residual 20% is split among remaining activities. Table X.7 displays total innovation investments by firm size. As expected, the participation over total investments increases with firm size: small firms (more than 30% of the sample) contributes only with 4.2% of innovation investments, and medium-small firms with less than 4%, while to medium and medium-large firms correspond 13% and 23%, respectively; as in the case of employment, large firms contribute for more than 55% of total investments. Equipment acquisition represents the larger share of investment in all firm groups, and despite the fact that a larger share of large firm has declared to perform R&D activities, Equipment acquisition remains the core of large firm investments, absorbing almost 60% of large firms' expenditures. Interestingly, small firms are an exception in this pattern: more than 50% of their investment is dedicated to Industrial design. Two different reasons may account for this charachterstic. First, small firm face more financial constraints in financing R&D or other innovation activities; this produces a bias in favor of other activities, such as Industrial design. Second, this bias may be strengthened by the fact that more than 70% of small manufacturing firms operate in low and medium-low technological intensity sectors, with rather similar processes and standardized non-technological productions. Thus, it is intuitive that these firms, more than investing in sophisticated R&D or professional trainings, concentrate their efforts in diversifying their products.[7]

Figure X.2
Investment in innovation activities
(*Percentages*)



Source: Authors' own elaboration based on ENIT 2005.

7 In terms of financial sources for innovation, more than 2/3 of total investments are financed with firm internal resources, mainly reinvestment of profits, while the relevance of loans and credits from private and commercial banking is limited (18%). Additionally, data shows that the percentage of firms using financial resources for innovation activities rises as firm size increases.

Table X.7

Investments in innovation activities by firm size

(*Percentages*)

Activity / Firm size	**Small (50<)**	**Medium-small (51-100)**	**Medium (101-200)**	**Medium-large (202-500)**	**Large (>501)**
Share of total investment	4.2	3.1	13.3	22.73	56.5
Internal R&D	4.5	18.0	17.9	22.4	17.3
External R&D	0.6	1.2	0.6	1.2	2.4
Equipment acquisition	23.6	56.0	61.6	56.1	59.4
Hardware acquisition	1.5	4.9	2.5	2.9	3.7
Software acquisition	0.6	3.7	3.4	2.7	1.8
Disembodied technology	0.7	4.5	5.0	6.5	3.1
Training	0.8	2.9	1.3	1.0	1.7
Industrial design	53.7	5.2	5.6	5.2	4.7
Consulting	13.5	3.2	1.7	1.6	5.4

Source: Authors' own elaboration based on ENIT 2005.

The second section of ENIT also collects information about innovation outcomes (Table X.8). As expected, participation of innovative firms increases with firm size: 24% of small firms implement innovations in product and processes, organization or product commercialization, but this participation rises up to 64% in large firms. Independently from firm size, innovative firms seem to prefer innovation in product and processes, followed by innovation in organization and distribution method. The pattern that emerges suggests that large firms obtain more results in terms of innovation outcomes, given their deeper involvement and more relevant investments in innovation activities such as R&D. Moreover, large firms have more complex organization and management structure, which make it more necessary to undertake organizational innovations (which includes introduction of new managerial methods, reorganization of work, adaptation of functional structure, or any other relevant change in the relation with third firms and with the public sector); this contributes to explain why this type of innovation if often observed in these firms. Still, organizational innovation is less frequent as an innovation outcome than product and process innovation, but more than innovation in product distribution. Thus, large firms are in general more likely than small and medium firms to implement organizational innovation.[8]

8 In relation to appropriability mechanisms, larger firms are more likely to apply and to obtain patents, which is consistent with their higher level of investment and participation in innovation activities (see Table X.8). However, large firms have applied and have obtained almost the same number of patents of medium and medium-large firms, although these firms are investing much less than large firms in innovation. Finally, small firms participate with less than 10% of patent applications and of patent obtained.

Table X.8
Innovation outcomes by firm size
(*Percentages and number*)

Innovation outcome / Firm size	Average	Small (50<)	Medium-small (51-100)	Medium (101-200)	Medium-large (202-500)	Large (>501)
Innovative firms (at least 1 of outcomes listed below)	42.4	24.4	40.7	47.8	57.4	63.7
Technological innovation	39.7	21.9	37.4	45.4	56.2	58.6
Product innovation	31.2	17.2	30.2	35.7	42.5	47.7
Process innovation	31.8	17.2	28.9	35.9	46.0	50.0
Organizational innovation	17.9	11.0	17.2	17.6	25.4	28.7
Selling and distributing methods innovation	9.6	5.7	8.1	10.1	14.4	15.5
Firms applying for patent applications	2.8	1.3	2.6	3.7	3.0	5.7
Firm obtaining patent application	1.8	0.7	2.2	2.4	1.1	4.0
Number of patents applied	146	12	48	29	29	28
Number of patents obtained	86	7	38	15	10	16
Number of firms	1 670	523	307	403	263	174

Source: Authors' elaboration on the basis of ENIT 2005.

The third section of ENIT collects information on ICT use and the characteristics of ICT investments. Table X.9 shows that ICT investment increases monotonically with firm size. However, investment behavior in ICT turns out to be much more polarized than investment in other activities for innovation. In fact, the difference between the percentage of small and large firms investing in ICT is much larger: small firms does not even reach 17% of firms investing in ICT. The fact that large and medium-large firms are more likely to invest in ICT might be based on different interpretations. First, most of small firms are involved in non-technologically sophisticated and rather standardized products, which do not imply a large use of ICT in production processes as in production-related activities. Second, as already noted, these firms are not particularly keen to invest in R&D or other research activities that might require a more intensive use of ICT. Third, the number of employees in small firms is quite reduced, so they do not require complex organizations to support the distribution of duties and competencies, which can be better managed with the help of specific software solutions. Fourth, given their financial constraints, small firms may prefer to concentrate investments in other kind of activities that they perceive as more effective in terms of profitability and competitiveness and that are less expensive and less affected by depreciation than ICT, such as Industrial design.

Large firms are more likely to complement ICT investments with other activities: in 70% of investing firms ICT investments come along with training activities, 60% with development or adoption of software and 51% with organizational change. Data also show that organizational change has much to do with changes in the organization of work rather than in firm structure (when organizational change is a consequence of ICT investments), and this phenomenon involves mainly large and medium-large firms. Indeed, less than ¼ of medium, 1/5 of medium-small and 10% of small firms declare to have undertaken organizational changes together with ICT investments. Once again, this could be linked with managerial and organizational problems that are typical of big and articulated organizations such as large firms.[9] Table X.10 reports other ICT indicators by firm size, like the ICT employees and availability of computing equipment. Data are consistent with the pattern of ICT investments firm groups showed in Table X.10. Indeed, the difference between the share of employees dedicated to ICT activities in small rather than in medium-large and large firms is huge, as is the difference between number of computers per firm and per employee across different firm groups.

Table X.9

ICT and complementary investments by firm size

(*Percentages*)

Activity / Firm size	**Average**	**Small (50<)**	**Medium-small (51-100)**	**Medium (101-200)**	**Medium-large (202-500)**	**Large (>501)**
Firms that invested in ICT	45.0	16.8	37.7	53.6	67.6	87.3
ICT complementary investments:						
Training	28.0	7.8	17.9	31.2	46.7	70.1
Organizational change	24.7	8.0	21.8	27.5	38.7	52.8
Changes in organization of work	23.5	7.4	21.1	26.5	35.7	51.1
Changes in organization structure	6.5	2.2	3.5	7.6	9.5	17.2
Changes in strategic orientation	3.3	1.7	1.9	3.9	3.8	8.6
Development of software/specific system	25.5	6.3	18.8	29.2	43.7	62.6
Adoption of standard software	25.9	7.6	21.5	29.7	36.5	59.2
Number of firms	1 670	523	307	403	263	174

Source: Authors' elaboration on the basis of ENIT 2005.

[9] Interestingly, in any firm group (with the exception of small firms), the percentage of firms that declare to have undertaken organizational changes related to ICT investments is significantly larger than the share of firms that report organizational innovations in the second section of the ENIT (see Table X.8). One possible explanation is that firms may tend to report organization innovations only when it implied radical changes and important re-definition of the organization of work or firm structure, while when asked about organizational change as consequence of ICT firms may include even little adjustment of duties assigned or changes in commercialization and selling methods.

Table X.10
ICT indicators
(Percentages and number)

Indicator / Firm size	Average	Small (50<)	Medium-small (51-100)	Medium (101-200)	Medium-large (202-500)	Large (>501)
Firms with ICT dedicates employees (%)	60.4	27.5	54.0	96.4	88.9	95.9
ICT employees over total (%)	1.8	2.1	1.4	1.3	1.2	2.2
Computers per firm (average)	84.0	7.1	22.4	43.1	99.9	492.5
Computers per employee	0.35	0.29	0.31	0.29	0.31	0.39

Source: Authors' elaboration on the basis of ENIT 2005.

Table X.11 refers to the access to the Internet and the kind of Internet connection used. The percentage of firms using the Internet reaches 100% in the case of large and medium-large firms considered in the survey, but the percentages are quite high in any group. Data about the Internet connection used show a large variability across groups of firms: xDLS is relatively more used by any kind of firm, while large firms seem to relatively prefer cable and optical fiber, and to a less extend XDLS and other channels; analogic modems are significantly used only by small and medium-small firms. This pattern is of course related to the costs to access a specific technology (which in turn depends on the scale) and to the speed of connection required by the firm to perform its activities: it makes sense that still ¼ of small firms prefer to use the analogic modem, since its reduced speed of connection is not a problem and is sufficient to satisfy the limited level of sophistication of this group of firms in terms of ICT use in production processes and organization.

Finally, ENIT 2005 also presents information concerning Internet use (see Table X.12), that is particularly useful in order to have an idea about the real incidence of ICT on firm activities. First thing to be noted is that large and medium-large firms seem to use the Internet for a much broader set of activities than other groups of firms: almost all large firms communicate and exchange information about their products (probably including digital marketing) via Internet, while around 90% of them have a web site (or under construction at the time of the survey), communicate with the Government or other public institutions and use e-banking services. Most small firms use the Internet to communicate (e-mail), followed by exchanging information about their products, e-banking services and receiving information from the Government. The use of the Internet in delivering customer services seems to be rather marginal in any group of firms, while large firms present the largest percentage of firms whose use of the Internet is related to R&D activities.

Table X.11
Access and availability of Internet
(Percentages)

Indicator / Firm size	Average	Small (50<)	Medium-small (51-100)	Medium (101-200)	Medium-large (202-500)	Large (>501)
Firms using Internet (%)	95.1	87.1	96.7	98.0	100.0	100.0
Internet connection:						
Analogic modem	15.2	24.4	16.9	10.4	8.3	5.7
xDLS (ADSL, SDSL, VDSL...)	44.1	37.6	51.7	51.8	44.8	31.0
Cable/optical fiber	22.9	16.2	15.9	20.6	30.0	48.8
Mobil access	2.2	1.7	2.9	2.2	2.2	2.8
Nomadic access (Wi-Fi)	7.9	6.3	8.4	9.1	8.7	7.4
Other (satellite...)	9.1	2.8	3.9	11.1	16.7	20.6
Other net connections:						
LAN	76.7	48.3	80.7	87.8	96.2	97.7
Intranet	44.0	23.3	37.4	49.1	59.7	80.4
Extranet	19.2	6.6	14.9	19.8	28.9	46.5

Source: Authors' elaboration on the basis of ENIT 2005.

Table X.12
Internet use by firm size
(Percentages)

Internet use / Firm size	Average	Small (50<)	Medium-small (51-100)	Medium (101-200)	Medium-large (202-500)	Large (>501)
Web site/under construction	69.9	47.2	69.7	80.4	85.1	89.6
Buying/selling/commercialization	52.1	46.8	51.7	53.1	54.7	62.0
Communication (e-mail)	92.4	84.5	93.8	95.5	96.5	97.7
Exchanging information about products	83.3	70.5	82.4	87.5	93.1	96.5
Receiving information from Government/other institutions	70.8	52.5	72.9	76.4	82.5	89.0
Information about R&D	37.7	18.3	32.5	43.4	53.6	67.2
E-banking	78.5	59.4	80.1	86.3	92.4	91.9
Transactions with Government/other institutions	53.4	32.1	55.7	62.7	66.1	71.2
Customer services	40.6	33.6	40.0	39.7	46.7	54.0
Products delivery/distribution	5.6	3.6	7.1	5.2	6.0	9.2
Other	52.0	44.5	47.5	56.3	60.4	58.0

Source: Authors' elaboration on the basis of ENIT 2005.

In sum, the ENIT 2005 offers a rather complete picture of Argentinean manufacturing sector. In particular, the survey describes firm behavior in terms of innovation investments, innovation outcomes and firms' availability and use of ICT. Nevertheless, information collected by ENIT 2005 also has some drawbacks when it comes to perform an empirical analysis. A first limitation is the sample size: despite being representative at national level, after cleaning up the data, just 1,670 observations are available, that is a quite small number to describe the whole universe of Argentinean manufacturing firms. Second, the survey does not provide detailed information about the quality of human capital; it lacks a detailed description of previous education or a clear specification of duties performed, especially when related to ICT use. Concerning ICT in firms, a third limitation is the lack of detailed information about the amount invested in ICT. In fact, the survey asks whether firms invest in ICT but it does not investigate how they invest (thus, if equipment, and which kind of equipment) nor how much. However, firms declare their investments in hardware and software, and this can be reasonably used as a proxy for ICT investments. Fourth, firms report about using Internet but not about use intensity: in other words, it is possible to know if firms commercialize their products via the Internet, but not which proportion of sales is distributed in this way. Hence, the relevance of the Internet may be misestimated, potentially affecting the soundness of the results of an empirical analysis.

4. Empirical model

Main hypotheses

This work aims at studying the effect of ICT on firms' productivity by analyzing the "direct" as well as "indirect" impacts of human capital, technological innovation and organizational change, and by testing the relevance that complementarity may have in affecting and strengthening this relationship. Thus, following the relevant literature, we argue that better skilled human capital and the implementation of organizational changes may strengthen the effect of ICT investments on firm productivity; beyond this, due to further complementarities among these factors, the impact of human capital or innovation on productivity may be amplified in presence of organizational changes. Following the literature, we specify a Cobb-Douglas production function based on the following specification:[10]

$$LnSs/L_i = \alpha_0 + \alpha_1 \, LnK/L_i + \alpha_2 \, LnL_i + \alpha_3 \, LnSK_i + \alpha_4 \, LnK_{ict,i} + \alpha_5 \, LnInn_i + \alpha_6 \, LnOC_i + \alpha_7 \, LnZ_i + \varepsilon_i \quad (1)$$

[10] Table A.2 in Appendix reports a summary of the main variables used in the literature.

where *LnSs/L* is the logarithm of total sales over employment (that proxies firm productivity); *LnK/L* is the logarithm of machinery and equipment investments per employee; *LnL* is the logarithm of the number of employees; *LnSK* is the logarithm of the percentage of employees with professional qualification (as a proxy for human capital); LnK_{ict} represents variables related to ICT capital; *LnInn* corresponds to innovation variables; *LnOC* represents organizational changes, and *LnZ* includes other control variables. Following this specification, we perform an empirical analysis on the base of the information available within ENIT 2005.

Concerning ICT-related variables and other non-traditional variables, the proxies used have been obtained as follows. First, we use the logarithm of the amount invested in hardware over total firm employment ($LnICT_{H}$,) as rough proxy for ICT access (Becchetti *et al.* 2003). A relevant shortcoming of this proxy is that it refers only to the amount invested in 2005; thus, it better represents an “ICT flow expenditure” rather than the real “ICT stock” available. In order to obtain a better variable to control for the magnitude of ICT use, we also use the number of computers per employee or the share of employees that have declared to use a PC in their everyday work ($LnICT_{EMP}$) (see Bresnahan *et al*. 2002; Arvanitis, 2005). Second, we also use the access and use of Internet as relevant ICT variables. The quality of access is expressed by a set of dummy variables related to the type of connection: *ICT_Mod* (analogic modem); *ICT_xDSL* (ADSL, SDSL, VDSL...); *ICT_Cab* (cable, optical fiber); *ICT_Ma* (mobile access); *ICT_ Na* (nomadic access, as Wi-Fi) and *ICT_other*. About Internet use, we focus on those uses that are more likely to be related to a modification (or adaptation) of firm organizational or functional structure, such as uses that imply commercialization, marketing or distribution. In fact, it is likely that the complementarity of organizational change could emerge especially through this kind of activities, reinforcing the impact of ICT on productivity. With this purpose, we introduce two dummy variables (*ICT_e-sell, ICT_e–buy)* that takes the value of 1 (0 otherwise) when the firm declares to have sold or bought products through the Internet, respectively.

Third, given the hypothesis of a possible relationship between ICT investment and innovation activities (Becchetti *et al*. 2003; Gargallo-Castel and Galve-Górriz, 2007b), we introduce a dummy variable (*INN*) which takes value of 1 if the firm declared to have implemented product or process innovation, 0 otherwise. Fourth, to control for organizational change, we use a dummy variable (*OC*) that takes the value of 1 if the firm declared to have undertakes organizational innovations, 0 otherwise (Black and Lynch, 2001; Giuri *et al.* 2008). This dummy variable has been created based on the answer about organizational innovation related to ICT investments (see Table X.9): consequently, this variable is not independent from ICT. The ENIT does not provide further information about the characteristics of organizational change undertaken, nor about how deeply it has modified production routines or managerial structures. Thus, it is not possible to create other variables which could take into account the “qualitative aspects” of organizational change.[11]

Finally, among other control variables, we include information on firm size, technological sector, geographical location, export and being part of an economic conglomerate. Firm size is captured by a set of dummy variables: *Sz_sm* (up to 50 employees; base categoy); *Sz_ms* (between 51 and 100); *Sz_md* (between 101 and 200); *Sz_ml* (between 201 and 500) and *Sz_lr* (more than 501). A second set of dummy variables controls for sector technological intensity: *Sec_low* (low technological intensity; base category); *Sec_melw* (medium-low technological intensity) and *Sec_medhg* (medium-high technological intensity); *Sec_hg* (high technological intensity). The dummy *BA* takes a value of 1 if the firm is located in Buenos Aires (urban area), and 0 otherwise. Finally, the dummy *Exp* takes value of 1 if the firm exports to foreign markets (0 otherwise), and the dummy *Group* takes values of 1 if the firm is part of an economic conglomerate (0 otherwise).[12]

5. Empirical analysis

In this section, econometric results are discussed. First, we analyze the “direct” impact of ICT, human capital and organizational change on firm productivity by performing OLS estimates. In order to check the relevance of organizational change, we perform a Chow test to verify the hypothesis of a pooled model versus a model which considers two sub-samples, separating firms that undertake organizational change from those which did not. Then, we display the evidence for “indirect” effects on productivity, testing the complementarity hypothesis between ICT, human capital and organizational change.

We consider a standard estimation model, whose results are reported in Table X.13. Each column presents a different specification, and we progressively add more variables to the basic model (column 1). The acquisition of machinery and equipment (*LnK/L*) is positive and significant in any specification, revealing the importance of capital in affecting labor productivity. The proxy for ICT expenditures ($LnICT_H$) is not significant in

[11] The ENIT survey does not provide a univocal definition of organizational change. The definitions of “organizational innovation” and “innovation in selling methods and distribution” (see Table X.8) cannot be overlapped to the concept of “organizational change” related to ICT investments (see Table X.9). This gives rise to a misevaluation of which is the magnitude of organizational change in Argentinean manufacturing firms. Moreover, by asking about organizational change as a consequence of ICT, the survey originates a relationship between organizational change and ICT that complicates the interpretation when it comes to explain its relevance on ICT impact over firm productivity. In fact, when organizational change is related to ICT investments, the possible correlation between ICT and organizational change cannot be interpreted without controlling for the presence of ICT.

[12] The ENIT does not provide information about firm age, so it is not possible to control for this characteristic. This may represent an important omitted variable, since firm experience is an important dimension for the hypothesis of complementarity (see Black and Lynch, 2001; Hempell, 2002; Becchetti *et al.*, 2003).

any specification.[13] Given that this variable may not be the most adequate to evaluate ICT impact on productivity, we try to add other ICT-related variables in the estimations. Following Bresnahan *et al.* (2002) and Arvanitis (2005), we introduce the variable $LnICT_{EMP}$, which measure the percentage of employees using a PC in their everyday activity.[14] Consistently with the literature, the coefficient associated to this variable is positive and significant, and robust to different specifications (see Table X.13). It means that a higher intensity of ICT use in a firm results in a higher productivity level.

The second specification (column 2) includes human capital (*LnSK*). The results show a positive relationship between this variable and labor productivity (as found in previous literature), and it is robust to the inclusion of other covariates. The third specification (column 3) includes the dummy for organizational change (*OC*): the variable has a positive sign, implying a positive impact of performing organizational changes over labor productivity, but it is significant only at a 10% level. As previously stated, this variable is not independent from ICT investment, making it necessary to control for ICT investments in the specification.[15] Another limitation of this proxy includes the fact that it does not take into account organizational changes not related with ICT investment, as the ENIT does not allow for obtaining a qualitative description of organizational change, since it does no distinguish between different types of organizational change. The fourth column presents the specification adding the dummy for innovation (*INN*), whose coefficient is positive and significant at 5%, which implies that innovative firms tend to be more productive than non-innovative firms.

Given the fact that the dependent variable is in logarithm, the coefficients of capital, ICT use and human capital skills (also in logarithms) can be interpreted as elasticities. Thus, in the fourth specification, a 1% increase in capital per employees induces a 2.7% increase in labor productivity, on average and *ceteris paribus*. Similarly, a 1% increase in the percentage of employees using PC in their everyday routine implies an increase of 8.9% on labor productivity, on average and *ceteris paribus*. Finally, firms that undertook organizational change are 12.2 % more productive than firms that did not implement organization change, while innovative firms are 14% more productive than firms that did not introduce any innovation, on average and *ceteris paribus*.

Concerning other covariates, the geographical dummy variable for firms located in Buenos Aires (*BA*) is not significant, while the productivity of exporting firms (*Export*) or are part of a group (*Group*) seems to be statistically more productive. Regarding technological intensity, the dummy for medium-high technological intensity is the only one significant

[13] This result is also discussed in Becchetti *et al.* (2003).

[14] We include the variable of ICT flow investment in hardware in all specifications, despite the fact that it is always not significant, since the way in which the measure of organizational change is defined is not independent form ICT investments. Hence, to identify the effect of organizational change on firm productivity beyond the effect of ICT investment, we had to include it in the estimations.

[15] See the discussion in Bertscheck and Kaiser (2003) and Giuri et al (2008).

and positive in any specification. About the Internet connections, the dummies of xDSL and cable connection are positive but with different significance levels, implying that more sophisticated Internet connections rather than standard modem connection are likely to have a positive impact on labor productivity. This could also be related with firms' attitudes towards technology: it is likely that firms that decide to contract xDLS or connect Internet by cable, in spite of doing by basic modem connection, could be more "technological friendly" or consider technology as a key factor in their development and competitive strategies. Finally, it is interesting to understand why the dummy associated to purchases via Internet (*ICT_e-buy*) is not significant, while the dummy for sales through the Internet (*ICT_e-sell*) is fully significant and negative. These results imply that the productivity of a firm that sells via Internet turns out to be (on average and *ceteris paribus*) 14.7% lower than a firm that does not use this commercial channel. Although this could be seen as counterintuitive, it may be explained by the fact that a firm that sells its products through the Internet enters in a broader and more competitive market where there are many other firms that sell the same products; hence, in order to be more competitive, they must reduce prices, reducing their sales per employee.

The use of a dummy variable for organizational change allows only for a shift in the intercept, but does not consider other possible effects of organizational change, such as difference in the parameters of other variables between firms that perform and firms that didn't perform organizational change. We implement a Chow test to evaluate the validity of the pooling assumption by separately estimating two regressions for the sub-samples of firms where organizational change had or had not been introduced (See Table A.3 in the Appendix). The Chow test rejects the pooled model which brings together firms that performed organizational change with those which did not, suggesting that the inclusion of a simple dummy for organizational change may not be sufficient to capture the differences in productivity between the two sub-samples. This result is coherent with what was argued by Milgrom and Roberts (1990) and Bertscheck and Kaiser (2003), whose work is based on the assumption that workplace reorganization does not only act as a shift parameter in the production function but changes –due to complementarities between workplace reorganization and input factors - the partial productivities of labor, ICT-capital and non-ICT-capital as well.[16]

Another interesting point to be highlighted about the separate model regards the different significance of the coefficients across the two regressions. While in the sample of firms that have not performed organizational change all variables that had significant coefficients in the pooled model maintain their significance level, the relevant variables that result to be still significant for firms that have implemented workplace reorganization are the dummies for group, export and ICT use (see fourth column of Table X.13 and Table A.3 in the Appendix). Thus, in presence of organizational change, the most important factor in affecting productivity

[16] Data availability for Argentinean manufacturing firms does not allow performing the empirical analysis proposed by Bertscheck and Kaiser (2003), who applied a switching regression model and Kernel density estimations.

turns out to be the use of ICT among employees. This result suggests that a complementarity between ICT use and organizational change may exist in firms that have decided to reorganize their work structure, independently form the level of human capital.

The second part of the empirical analysis aims at finding evidence of the existence of complementarity between organizational change, human capital and ICT. Following Arvanitis and Loukis (2009) and Giuri *et al.* (2008), we test the hypothesis of complementarity by introducing alternatively interactions terms in the empirical model, which represent the idea that the effect of ICT on firm productivity is increased when associated with human capital and/or organizational change (see Table X.14). Given its significance level, we use the percentage of employees using a PC in their duties as proxy for ICT use. The first model includes an interaction term between ICT and human capital; the second, the interaction between ICT and organizational change; the third, the interaction between human capital and organizational change; and the fourth includes all variables, all pair-wise interactions terms and one interaction term for the three factors. The econometric results provide evidence in favor of the hypothesis of complementarity between ICT, human capital and organizational change, even if pair-wise complementarity is not found in every possible association. However, results have to be interpreted with caution, since, as it was argued by Ichniowski *et al.* (1997), estimates of pair wise interaction effects may be “too simplistic” and ignore more complex linkages among more than two complements. At the same time, putting all the interaction terms inside the regression could lead to collinearity problems.

Signs of the coefficients of all interaction terms are positive as expected, while their significance level differs across specifications. In the first column of Table X.14, the interaction term between ICT use and human capital is positive and significant. The same can be observed in the second column, where the interaction term between ICT and organizational change is positive and significant, leaving unchanged relevance and sign of other coefficients. These findings suggest the existence of complementarity between ICT and human capital, and between ICT and organizational change. Thus, to express its potential in terms of impact on productivity, the introduction of ICT should come along with improvements on skill and organizational structure.

This positive evidence is not found in the case of the interaction between human capital and organizational change, reported in the third column. This finding does not reduce the importance of human capital in affecting positively firm productivity and in strengthening the impact of ICT, but it may raise some doubts about the existence of a skill-based organizational change effect. In other words, this result does not support the hypothesis that the adoption of workplace reorganization calls for more skilled employees, and vice-versa; thus, the impact of organizational change in Argentinean manufacturing firms’ productivity is likely to be more relevant if it comes along with ICT ithan to the level of human capital. This result confirms what is suggested from the Chow test: organizational change seems to have a significant effect on firm productivity only when it relates to ICT, at any given level of human capital.

Finally, the coefficients reported in the fourth column support the hypothesis of full complementarity among ICT, human capital and organizational change: the coefficient of the interaction term among all three factors is positive and significant. In this last model, the interaction term between ICT and organizational change remains significant, while the interaction between human capital and organizational change is now positive and significant, but at lower level; the interaction between ICT and human capital becomes non significant. Hence, in Argentinean manufacturing firms, organizational change seems to reinforce the positive association between ICT use and productivity.

Table X.13
OLS estimations

Variables	Model 1		Model 2		Model 3		Model 4	
LnL	-0.058	(0.071)	-0.093	(0.074)	-0.099	(0.074)	-0.095	(0.074)
LnK/L	0.021	(0.007) ***	0.019	(0.007) ***	0.020	(0.007) ***	0.027	(0.007) ***
$LnICT_{EMP}$	0.100	(0.016) ***	0.088	(0.016) ***	0.089	(0.016) ***	0.089	(0.016) ***
$LnICT_{H}$	0.006	(0.006)	0.004	(0.005)	0.003	(0.006)	0.005	(0.006)
LnSK			0.029	(0.006) ***	0.028	(0.006) ***	0.029	(0.006) ***
OC					0.100	(0.059) *	0.115	(0.059) *
INN							0.133	(0.056) **
BA	0.006	(0.050)	0.058	(0.049)	0.059	(0.050)	0.051	(0.050)
Group	0.573	(0.063) ***	0.552	(0.063) **	0.550	(0.063) ***	0.553	(0.062) ***
Export	0.592	(0.059) ***	0.566	(0.059) **	0.564	(0.058) ***	0.567	(0.058) ***
Sz_ms	0.032	(0.100)	0.016	(0.100)	0.016	(0.099)	0.014	(0.100)
Sz_md	-0.094	(0.138)	-0.110	(0.140)	-0.110	(0.139)	-0.109	(0.140)
Sz_ml	-0.053	(0.183)	-0.038	(0.186)	-0.043	(0.185)	-0.037	(0.185)
Sz_lr	0.081	(0.261)	0.130	(0.266)	0.122	(0.266)	0.121	(0.266)
Sec_melw	0.132	(0.068) *	0.107	(0.068)	0.106	(0.068)	0.109	(0.068)
Sec_medhg	0.168	(0.062) ***	0.135	(0.063) **	0.127	(0.062) **	0.141	(0.062) **
Sec_hg	-0.057	(0.079)	-0.098	(0.078)	-0.099	(0.078)	-0.070	(0.080)
ICT_e-sell	-0.168	(0.054) ***	-0.162	(0.054) ***	-0.162	(0.054) ***	-0.160	(0.053) ***
ICT_e-buy	-0.031	(0.053)	-0.039	(0.054	-0.046	(0.054)	-0.040	(0.053)
ICT_xDSL	0.175	(0.065) ***	0.165	(0.064) **	0.160	(0.065) **	0.160	(0.064) **
ICT_Cab	0.387	(0.074) ***	0.372	(0.073) ***	0.367	(0.073) ***	0.366	(0.073) ***
ICT_Ma	0.299	(0.171) *	0.259	(0.166)	0.251	(0.165)	0.246	(0.163)
ICT_ Na	0.095	(0.081)	0.085	(0.080)	0.081	(0.080)	0.090	(0.080)
ICT_other	0.384	(0.097) ***	0.370	(0.095) ***	0.361	(0.095) ***	0.367	(0.095) ***
constant	11.721	(0.238) ***	12.048	(0.254) ***	12.067	(0.255) ***	11.948	(0.260) ***
Obs.	1 670		1 670		1 670		1 670	
F	31.00		30.91		31.16		30.34	
R-squared	0.294		0.3052		0.3063		0.3083	

Source: Author's own elaboration.
*Note: *, **, *** denote statistical significance at 1%, 5% and 10%, respectively.*

Table X.14

OLS estimations: complementarity hypothesis

Variables	Model 1		Model 2		Model 3		Model 4	
LnL	-0.078	(0.073)	-0.063	(0.072)	-0.089	(0.073)	-0.082	0.073
LnK/L	0.025	(0.007) ***	0.026	(0.007) ***	0.026	(0.007) ***	0.026	0.007***
$LnICT_{EMP}$	0.137	(0.029) ***	0.094	(0.015) ***	0.090	(0.015)	0.114	0.028***
$LnICT_{H}$	0.006	(0.005)	0.006	(0.006)	0.004	(0.006)	0.004	0.006
LnSK	0.042	(0.008) ***			0.026	(0.006) ***	0.036	0.008***
OC			0.461	(0.102) ***	0.242	(0.104) **	0.710	0.179***
INN	0.131	(0.054) **	0.109	(0.056) *	0.123	(0.056) **	0.139	0.055**
I_ictskll	**0.005**	**(0.002) ****					**0.003**	**0.002**
I_ictoc			**0.261**	**(0.055) *****			**0.381**	**0.082*****
I_skiloc					**0.039**	**(0.031)**	**0.110**	**0.064***
I_tot							**0.048**	**0.019*****
BA	0.043	(0.049)	0.037	(0.050)	0.048	(0.050)	0.024	0.049
Group	0.538	(0.063) ***	0.549	(0.063) ***	0.546	(0.062) ***	0.513	0.063***
Export	0.558	(0.058) ***	0.585	(0.058) ***	0.567	(0.058) ***	0.556	0.058***
Sz_ms	0.008	(0.099)	0.038	(0.099)	0.002	(0.098)	0.011	0.098
Sz_md	-0.125	(0.139)	-0.078	(0.138)	-0.126	(0.138)	-0.116	0.138
Sz_ml	-0.059	(0.185)	-0.032	(0.183)	-0.058	(0.183)	-0.045	0.183
Sz_lr	0.094	(0.265)	0.082	(0.260)	0.087	(0.262)	0.075	0.261
Sec_melw	0.115	(0.067) *	0.124	(0.067) *	0.106	(0.067)	0.102	0.067
Sec_medhg	0.140	(0.062) **	0.168	(0.062) ***	0.145	(0.062) **	0.122	0.062**
Sec_hg	-0.082	(0.080)	-0.052	(0.080)	-0.072	(0.079)	-0.097	0.080
ICT_e-sell	-0.154	(0.053) ***	-0.163	(0.053) ***	-0.160	(0.053) ***	-0.156	0.053***
ICT_e-buy	-0.037	(0.053)	-0.029	(0.053)	-0.036	(0.053)	-0.036	0.053
ICT_xDSL	0.160	(0.064) **	0.165	(0.065) **	0.157	(0.064) **	0.153	0.063**
ICT_Cab	0.354	(0.072) ***	0.352	(0.075) ***	0.359	(0.073) ***	0.322	0.073***
ICT_Ma	0.249	(0.162)	0.276	(0.167)	0.240	(0.163)	0.222	0.160
ICT_ Na	0.087	(0.079)	0.085	(0.081)	0.087	(0.080)	0.074	0.080
ICT_other	0.357	(0.094) ***	0.345	(0.096) ***	0.363	(0.095) ***	0.298	0.094
constant	11.999	(0.264) ***	11.647	(0.246)	11.922	(0.258) ***	11.975	0.263***
Obs.	1 670		1 670		1 670		1 670	
F	28.60		29.74		28.18		27.21	
R-squared	0.314		0.305		0.310		0.322	

Source: Author's own elaboration.
*Note: *, **, *** denote statistical significance at 1%, 5% and 10%, respectively.*

6. Conclusions

This paper depicts a firm-level analysis on the impact of ICT, human capital and organizational change on labor productivity in Argentinean manufacturing firms. Besides the ICT "direct effect", this work aims at identifying the existence of complementarities among ICT, human capital and organizational change. The underlying idea is that ICT needs to come along with changes in human capital and workplace organization in firms, whose interaction produce an additional effect that reinforces the positive effect of ICT on firm productivity. In particular, organizational change is supposed to mediate and strengthen the joint impact of ICT and skill.

Our findings are consistent with the complementarity hypothesis. Nevertheless, interactions among ICT, human capital and organizational change can't be easily interpreted. First, empirical results show a positive "direct effect" of physical capital, human capital, ICT and organizational change on labor productivity. Second, the relevant literature suggests that studying the impact of organizational changes may require a more sophisticated analysis, since the implementation of some kind of workplace reorganizations may affect not just the intercept, but also the coefficients of other variables in the model. This indicates that workplace reorganization may induce a change in the entire set of output elasticities and in the set of variables capturing observable firm heterogeneity; hence, inserting a dummy variable for organizational change may not have fully revealed the effects of organizational change on productivity. Moreover, the outcomes of the empirical analysis suggest that the effect of organizational change may be more related to the ICT use than to the level of human capital. Finally, the empirical analysis displays evidence of two interaction effects (between ICT and human capital and between ICT and organizational change) and of threefold complementarity between ICT, human capital and organizational change.

An important shortage of this study is its lack of a dynamic perspective. This is relevant, since firms that decide to adopt complementary activities (ICT, human capital and organizational change) may require time to learn how to manage them, Therfore, the effects on productivity may be discerned only in the medium-long run. Moreover, the decision of undertaking an organizational change may not always be simultaneous with the decisions about ICT and human capital. Hence, an important follow-up for further analysis could be the introduction of time perspective in the empirical analysis, which would allow for performing fixed-effect to control for unobservable heterogeneity and to use lagged terms in order to reduce simultaneity problems. Overall, this may provide a more precise representation of ICT impact and organizational changes on productivity.

The results achieved in this study question which kind of policies should be implemented to benefit more from ICT use in the productive sector. Furthermore, this study shows that in order to appropriate benefits from new technologies such as ICT, other related factors must be considered: ICT by itself is not a *panacea,* and human capital skills as well as organizational changes or other innovative activities must be fostered in order to exploit complementarities. More generally, the production systems have to be considered with the complexity of relationships included, which require policies capable of managing complementarities between science and industry in such a way as to generate and spread knowledge, and improve productivity performance (Metcalfe, 1995; Cimoli *et al.* 2006). Thus, it is not only important to facilitate ICT access, but also to generate the necessary policies to use these technologies in a proper manner and to obtain the largest possible benefits, otherwise we could be running the risk of enlarging the structural heterogeneity in Latin American countries. In conclusion,, this study shows that it is not only about access and infrastructure, but also about capabilities and competences in order to take full advantages of new technologies.

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8. Appendix

Table A.1
Sectoral classification according to technological intensity

Sectors	Description
Low technology	Manufacture of food products and beverages, manufacture of tobacco products, manufacture of textiles, manufacture of wearing apparel; dressing and dyeing of fur, tanning and dressing of leather; manufacture of luggage, handbags, manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials, manufacture of paper and paper products, publishing, printing and reproduction of recorded media, manufacture of furniture; manufacturing n.e.c., recycling.
Low-medium technology	Manufacture of coke, refined petroleum products and nuclear fuel, manufacture of rubber and plastics products, manufacture of other non-metallic mineral products, manufacture of basic metals, manufacture of fabricated metal products, except machinery and equipment, and manufacture of railway and tramway locomotives and rolling stock.
Medium-high technology	Manufacture of chemicals and chemical products except manufacture of pharmaceuticals, medicinal chemicals and botanical products, manufacture of motor vehicles, trailers and semi-trailers, and manufacture of other transport equipment except building and repairing of ships and boats.
High technology	Manufacture of pharmaceuticals, medicinal chemicals and botanical products, manufacture of office, accounting and computing machinery, manufacture of electrical machinery and apparatus n.e.c., manufacture of radio, television and communication equipment and apparatus, manufacture of medical, precision and optical instruments, watches and clocks, and manufacture of motor vehicles, trailers and semi-trailers.

Source: Authors' elaboration.

Table A.2
Variables used in the literature

Specification of production function	**Cobb-Douglas**
Dependent variable	Productivity: - Sales per employee - Gross output per employee - Value added per employee - Change in value added - Total Factor Productivity - Distance from the “best practice” by using a stochastic frontier approach
Traditional independent variables	Capital (investment, stock) Labor (number of total employees)
Non-traditional independent variables	ICT: - ICT investment (total, per employee) - ICT capital stock - Investments in software, hardware and telecommunication - Access to a specific technology (dummy) - Number of PC (total, per employee) Human Capital in ICT: - ICT users (number, %) - Non-administrative staff of total employees - Share of employees working with Internet and Intranet connections Organizational change: - Organizational change (dummy) - Share of workers involved in team work, employees rotation, duties assignment Other control variables: - Cost of other inputs - Innovation - Ownership/affiliation - Sector (dummy) - Firm size - Firm age - Location

Source: Authors' elaboration.

Table A.3
OLS estimations by firm sub-samples

Variables	Organization change Coef.	Std. Dev.	No-organizational change Coef.	Std. Dev.
LnL	0.074	(0.175)	-0.141	(0.080)
LnK/L	0.015	(0.012)	0.028	(0.008) ***
$LnICT_{EMP}$	0.365	(0.075) ***	0.078	(0.016) ***
$LnICT_{H}$	-0.001	(0.009)	0.009	(0.007)
LnSK	0.028	(0.036)	0.028	(0.006) ***
OC	(dropped)		(dropped)	
INN	0.080	(0.099)	0.152	(0.068)**
BA	0.095	(0.095)	0.013	(0.057)
Group	0.477	(0.093) ***	0.549	(0.081) ***
Export	0.545	(0.121) ***	0.552	(0.066) ***
Sz_ms	0.137	(0.232)	0.028	(0.110)
Sz_md	-0.110	(0.284)	-0.063	(0.156)
Sz_ml	-0.239	(0.386)	0.088	(0.209)
Sz_lr	-0.335	(0.565)	0.323	(0.295)
Sec_melw	0.060	(0.119)	0.112	(0.080)
Sec_medhg	-0.024	(0.121)	0.185	(0.072) **
Sec_hg	-0.367	(0.146) **	-0.009	(0.094)
ICT_e-sell	-0.088	(0.099)	-0.185	(0.064) ***
ICT_e-buy	-0.173	(0.100)	-0.008	(0.063)
ICT_xDSL	0.004	(0.123)	0.227	(0.078) ***
ICT_Cab	0.119	(0.135)	0.418	(0.089) ***
ICT_Ma	0.298	(0.223)	0.280	(0.226)
ICT_ Na	0.204	(0.144)	0.025	(0.099)
ICT_other	0.261	(0.160)	0.353	(0.123) ***
constant	12.003	(0.820) ***	12.012	(0.277) ***
Number	414		1256	
F	9.07		22.01	
R-squared	0.348		0.291	
RSS	316.333		1 132.373	

Source: Author's own elaboration.
*Note: *, **, *** denote statistical significance at 1%, 5% and 10%, respectively.*
Chow Test: We run the OLS regression presented in column 4, Table X.13, for the sub-samples of firms that declared to have performed or no organizational change. We take the residual sum of squares (RRS) and the degrees of freedom (DF) of these two regressions (whose sum gives the RRS and the DF of the unconstrained model), and we use them together with the RSS and DF of the "constrained" or pooled model presented in Table X.14 in a F-test:

$$F = \frac{(\text{RSS pooled model} - \text{RSS unconstrained model}) \,/\, (\text{DF pooled} - \text{DF unconstrained})}{\text{RSS unconstrained} \,/\, \text{DF unconstrained}}$$

$$F = \frac{(1485.564 - 1448.712) \,/\, (1645 - 1622)}{1488.712 \,/\, 1622} = 1.794$$

The critical value for the F-statistics at the 0.05 significance level is $F_{24,\infty} = 1.75$. Thus, data reject the pooled model, suggesting that the inclusion of a simple dummy for organizational change may not be sufficient to capture the differences in productivity between the two sub-samples of firms.

C. ICT in Latin America: concluding remarks

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Information and Communication Technologies (ICT) are considered a driving force for information, technology and knowledge diffusion and, thus, an important engine for innovation and development. In this sense, the potential impacts of ICT diffusion over different development dimensions deserve a deeper analysis of its patterns. This will also strengthen the public policy design in order to promote ICT benefit dissemination across all population segments in the society. Nevertheless, in comparison to other policy making areas, the application of a broad-based range of measurement tools to understand the underlying forces that could influence policy decision-making in the Information Society development is especially important. The first reason is that even if there was an optimum way toward Information Society, the rapid pace of ICT development makes it unlikely to know such an optima, since the world will have moved on before they can be established (Miles, 2003). Given this challenge, it is important to implement proactive policies towards ICT diffusion having a comprehensive understanding on its determinants, characteristics and impacts. Secondly, even though ICT is the dominating general purpose technology nowadays, it still does not reach the level of maturity of other general purpose technologies, such as electricity or motorization. In this sense, the Schumpeterian creative destruction is still fast and strong in this nascent technological system. Indeed, from the emergence of the ICT paradigm, technical change has increased widely, creating new challenges and opportunities for economic growth.

In the last twenty years there have been several attempts to measure empirically the impact of ICT on economic development. Most of studies focuses on aggregate or country level analyses that correlates ICT capital and economic growth (*e.g.* Jorgenson, 2001). Despite the aggregate nature of these studies, empirical results —most of them based on “growth accounting methodology”— tend to confirm that ICT have a positive effect on economic growth. In Latin America, empirical evidence shows that ICT investments do affect productivity positively (Peres and Hilbert, 2009). However, this impact seems to be lower than ICT impact in developed and newly-industrialized countries. This result suggests that differences in *National Innovation Systems* (NIS) and their corresponding capabilities to create and disseminate knowledge within countries, are relevant aspects in order to explain the heterogeneous impact of ICT.[1] Indeed, it does seem that, in order to fully exploit the potential impacts of new technologies, it is necessary not only to have access to them, but also to develop key complementary aspects at different knowledge dimensions in the society. However, the main deficiency of this literature is that it does not provide any insights concerning the underlying mechanisms that can explain this relation. From this perspective, it seems essential to understand which are the latent channels connecting ICT with economic growth. Additionally, understanding these mechanisms facilitates the implementation of relevant policy recommendations. In Latin America, little is known about diffusion and impact of ICT at different microeconomic levels.

The evidence discussed in this book attempts to fill this gap by showing the benefits and limitations of microdata analysis at individual, household and firm levels. Section A - *ICT at Household Level in Latin America* displays evidence with respect to ICT diffusion based on *National Household Surveys*. Using this type of information allows us to understand ICT access and usage by different socio-economic dimensions and at different aggregation levels. At the same time, these surveys provide a wide set of socio-economic characteristics at individual and household levels that can be correlated with ICT access. One important limitation is that *National Household Surveys* do not provide detailed information on some technology diffusion dimensions, like ICT usage patterns. Additionally, different type of questions in each country creates difficulties to make international comparisons.

The different chapters of section A present important evidence concerning ICT diffusion. Chapter I - "*Determinants of ICT Access*"- analyzes ICT access patterns in Brazil, Chile, Costa Rica, El Salvador, Honduras, Mexico and Paraguay. It shows that computer adoption and Internet access is relatively low if compared with developed countries. Nevertheless, there are important differences across countries, showing a high degree of heterogeneity. Indeed, computer adoption and Internet access at household level is concentrated in narrowly defined segments of income, educational and groups living in urban areas in each country. Thus, diffusion of ICT seems to replicate other previous socio-economic inequalities in the region. Additionally, the comparative analysis shows that countries with lower ICT diffusion levels present higher penetration inequality across income and educational groups. Interestingly, econometric estimations also highlight the educational role of ICT, the presence of geographical network effects affecting ICT access and the complementarities between Internet uses at different locations (with the

[1] The concept of National Innovation Systems (NIS) emerged in the eighties to explain the differences in the innovative performances of industrialized countries. The underlying idea was that innovation differences were related to combinations and interactions of different institutions within the society. Among the dimensions that NIS includes in its framework are: characterization of innovation and learning as systemic, interactive and cumulative processes with multiple sources; re-conceptualization of the firm as a learning organization embedded within a broader but at the same time specific socio-economic-political environment, reflecting historical and cultural trajectories; relevance of taking into account the productive, financial, social, institutional and political spheres, as well as micro, meso and macro aspects in the society.

exception of Chile). By using the same microdata, Chapter II - "*Patterns of Internet Use*" focuses on the determinants of ICT usage patterns. In particular, it shows that traditional variables such as income, education and age are important determinants of ICT use at individual level. Additionally, females are found to be less likely to use the Internet, even once access is provided. Then, granting access does not necessarily mean to erase the gender digital divide. This suggests that the gender divide could be divided in *access divide* and *use divide*. Furthermore, analysis of single Internet applications provides evidence of a differentiated use by socio-demographic categories, suggesting that women and people located in rural areas could benefit more from Internet diffusion. These results open a set new questions regarding ICT. Indeed, while ICT access is still a main issue in the region, it is also important to consider that access does not translate into usage.

Focusing on ICT impact, Chapter III - "*Impact of Internet Use on Individual Earnings*" demonstrates an important and sizable return to Internet use for both salaried and self-employed workers in the six Latin American countries analyzed, which range between 18% and 30%. These returns are high compared with estimates for industrialized countries. This could be explained by the relative lower prevalence of Internet use in the region. Additionally, the evidence suggests that Internet usage at work and usage at home by salaried workers are complements with respect to their impact on earnings; and that there is a positive effect of Internet over earnings for self-employed workers who have ICT access neither at home nor at work. Finally, Chapter IV - "*Gender Differences in Internet Use*" focuses in the gender dimension of ICT. The descriptive statistics suggests that, on average there is a gender Internet use divide against women in the region, confirming the results of Chapter I. Indeed, it is observed that the gender divide is more frequent in urban rather than in rural areas; that it affects older women and that it is more prevalent in the middle and upper ends of household income distribution. Nevertheless, econometric results indicate that, controlling for different characteristics including geographic area of residence, age, education, income, labor market status, occupation and sector of activity, the gender gap in Internet usage is much lower and it does not seem to affect the Internet use probability at any place. Furthermore, gender digital divide is almost inexistent among individuals with less than 24 years old. But, even controlling for the same characteristics, on average and *ceteris paribus*, being a female reduces in up to 6% the probability of Internet use at home. Altogether, results suggest that gender digital divide does exist but it is mainly —but not all— a consequence of different men and women characteristics and gender socioeconomic inequalities.

The section B - *ICT and Firm Performance in Latin America* attempts to understand the impact of ICT on different firm performance measures in five countries. Some studies also analyze complementarities of ICT with organizational changes and human capital. One important difference with section A - *ICT at Household Level in Latin America* is that these studies do not provide a comparison among countries. Indeed, there are some statistical difficulties that prevent us to make cross-country comparisons.[2] First, temporal coverage of different surveys is not homogeneous. Second, access to the surveys is difficult because of statistical confidentiality. Indeed, in some countries it is only possible to develop research activities in the computers of the National Statistical Offices. Third, questions concerning innovation activities and ICT diffusion within firms have different characteristics in each country.

The studies in section B investigate the ICT impact on performance measures, like productivity and profitability, in manufacturing firms in Argentina, Chile, Colombia, Peru and Uruguay. For this purpose, empirical approaches attempts to identify not only the direct mechanism but also indirect channels of ICT impact over firm performance. These studies use a set of firm level variables related to technological capabilities (R&D investments, machinery and equipment investments, ICT investments), employment characteristics and several control variables (age, sector, export condition, regional location, among others). A common pattern observed in the different countries is a high level of heterogeneity in ICT use. In general, ICT use in small and medium-size enterprises is relatively lower than in large firms. The same pattern can be observed with respect to technological intensity: firms in knowledge intensive sectors have higher propensity to use ICT.

Regardless of econometric methodologies and inherent statistical problems faced by these quantitative analyses, the evidence tends to confirm that ICT and technological activities affects positively different firm outcomes, like labor productivity in Colombia, Argentina and Uruguay, and firm profitability in Peru. In Colombia and Argentina, econometric results also suggest that productivity gains are reinforced by investments in human capital and innovation activities. Additionally, in Argentina there is evidence of complementarities between ICT and organizational change on their effects on productivity. By contrast, in Colombia is not confirmed the hypothesis of complementarity between ICT with human capital and organizational changes. Interestingly, the empirical evidence for Peru suggests that it is through innovation activities that different technological resources affect firm profitability. Chapter IV, concerning the case of Uruguay, is the only empirical analysis that investigates the effects of ICT on employment levels. Remarkably, econometric results support the complementarity hypothesis between ICT investments and employment, even when only considering unskilled employees. This suggests that ICT offer important possibilities in creating new job opportunities. The evidence in Chile -based on a reduced firms sample and measuring only manager's perception of ICT impact- also shows that ICT affects different aspects of the productive processes. In particular, firms with higher ICT budget tend to associate production cost reductions to these technologies, although ICT employment is considered more an expense than an ICT effort to improve efficiency.

[2] The Statistical Offices implements National Innovation Surveys based on the Oslo Manual (1992) in the case of Brazil and Chile, and based on the Bogotá Manual (2001) in the case of Argentina, Colombia, Peru and Uruguay. In Chile, however, it was not possible to use the National Innovation Survey because of the absence of ICT relevant information.

Taking into account the limitations of ICT microdata analyses, there are some important avenues to work further. In the context of *National Household Surveys*, it seems important to implement additional questions concerning patterns of ICT use. Also, the construction of panel datasets would provide a more suitable empirical approach to understand ICT dynamic effects. Clearly, these can facilitate the study of the digital divide and the potential impacts of ICT at individual and household levels. Within the context of firms, it is relevant no only to redefine some questionnaires but also to implement them periodically. In some cases, for example in Chile, it is urgent to include ICT questions within the *National Innovation Surveys*. Additionally, it is important to implement innovation surveys with ICT dimensions to other sectors like services and agriculture. In an aggregate view, it is necessary to proceed towards the identification of a common set of ICT indicators, and to define a proper structure to develop them. It seems that *National Innovation Surveys*, with information on complementary dimensions such as innovation, R&D investments and technological capabilities, is the more suitable framework.

The public policy arena related to knowledge creation, innovation activities and diffusion of technologies is an important open avenue. Indeed, knowledge has some particular characteristics —like its public, systemic and transversal nature; low marginal costs of reproduction but high cost and uncertainty of original production; non linearity and increasing returns, heterogeneous degrees of tacitness (Stephan, 1996)— that call for proactive policy actions. In this sense, public policies should proceed towards an integral perspective which includes the different economic, social, cultural and technological dimensions. But at the same time, it is unavoidable to use microdata to analyze the latent microeconomic mechanisms that explain ICT diffusion and impacts.

In particular, the evidence presented in this book suggests several public policy areas in order to spread ICT benefits along all population segments. In terms of ICT diffusion, it is clear that ICT access is still an important issue in Latin America. This situation calls for proactive policies in order to promote ICT access to disadvantage population groups. Additionally, the evidence concerning the gender digital divide suggests that this will be reduced as long as other significant gender gaps are tackled. Indeed, most of the observed digital gender divide is associated to different socio-economic characteristic of women in the region, like their insertion in the labor force. Thus, proactive policies that facilitate female insertion in labor markets would also imply a reduction in the gender digital divide. Furthermore, given the fact that women in rural areas are relatively more prone to use the Internet than those in urban areas, developing Internet infrastructure in rural areas would then be helpful for a better insertion of women in the digital society. Additionally, it is important to consider that ICT access does not translate automatically into ICT usage. Thus, complementary policies which promote human capital and workers skills should also be an important dimension in order to exploit ICT benefits.

In the context of ICT at firm level, it is necessary that public policies take into account the high level of heterogeneity across firms. This heterogeneity encompasses not only firm characteristics (employment, size, age and sales, among others) but also performance measures (productivity, profitability, etc.) and innovation and technology related activities. Thus, selective economic policies, than can deal with these different firm scenarios and also different complementary resources (innovation activities, technological capabilities) would be more adequate to promote ICT diffusion and its positive impacts. For instance, large firms in technologically-advanced sectors exporting to international markets represent a completely different situation than informal micro firms that develop a standardized product for the local markets. Indeed, the lack of selective public policies can increase the technological and productivity gaps among firms, even in narrowly-defined firm groups and activity sectors. In this sense, it seems important to design science, technology and innovation policies for particular firms (*e.g.* exporters) but at the same time to proceed towards the modernization of the whole productive sector. For instance, the program “MiPyme Digital” developed by the Ministry of Information and Communication Technologies in Colombia. This program seek to reduce ICT access gaps across micro, small and medium firms by promoting the implementation of different technological solutions, hardware, software, Internet access and enhancing worker training.

Also, it seems particularly important to strengthening the relations between policy makers and academic scholars. This can have a direct impact on strengthening the capabilities of innovation and technology institutions within countries. Indeed, until now ICT microdata at both household and firm levels have been used by researchers to develop academic studies which are later published in international journals. However, microdata have not been used by policymakers in areas of science, technology and innovation. Furthermore, what scholars investigates have no particular interest for policymakers or empirical applications in the productive sector. In this sense, there is an important dissociation between who implements microdata surveys (National Institutes of Statistics); who used innovation surveys (researchers) and who implement economic policies (policymakers). It is essential to create a close relationship among them in order to facilitate knowledge, information and experience transfers. This would clearly enhance institutions capabilities and the process of design, implementation and evaluation of economic policies fostering innovation activities and diffusion of new technologies. This situation creates an important open field for proactive actions.

In terms of research agenda, there are important issues that can expand the actual understanding of ICT phenomena in the region. In the area of ICT at household and individual level, it seems particularly relevant to analyze to what extend ICT diffusion is expanding, or contracting, different socio-economic inequalities in Latin America. In fact, given that ICT access is heterogeneous among different population segments and that human capital and education levels affect potential benefits, ICT may become a new source of income, education, and opportunities inequality. In the area on firm level analyses, it seems worth to understand the reasons why firms do not have a more proactive role related to ICT investments, innovation and R&D activities. Indeed, having a more precise analysis on the relevance of potential market failures (including information asymmetries in credit markets), indivisibility problems or lack of cooperation activities, can improve public intervention. Another fruitful research area is related to the impacts of information diffusion on aspects like promotion of social programs, governance and political participation and entrepreneurship. Indeed, households, especially in rural areas where they are often not only consumers but also productive units, can gain several benefits from ICT, in terms of productivity and faster/cheaper communication with relevant markets. In particular, this area of entrepreneurship connects the role of ICT at individual-household and firm levels.

Additionally, Latin American countries should proceed towards strengthening the evaluation of innovation, technology and ICT-related policies. This aspect seems to be rather relevant, especially considering the low availability of resources, important opportunity costs and high social pressures on the resource allocation process in the region. A better understanding of these issues would clearly contribute to an enhanced design and implementation of public policies promoting ICT benefits in Latin America. As Papadakis (2001) pointed out, "*ICT have no reason to exist on themselves, but only on the consequences they have for individuals and their households*".

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